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CHRISTIANE MARA GOULART

UNOBTRUSIVE TECHNIQUE BASED ON INFRARED THERMAL IMAGING FOR EMOTION RECOGNITION IN CHILDREN- WITH-ASD-ROBOT INTERACTION

VITÓRIA

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Tese de Doutorado apresentada ao Programa de Pós-Graduação em Biotecnologia da Rede Nordeste de Biotecnologia (RENORBIO) do ponto focal Espírito Santo – Universidade Federal do Espírito Santo (UFES), como requisito parcial para obtenção do título de Doutora em Biotecnologia.

Orientador: Prof. Dr. Teodiano Freire Bastos-Filho

Coorientadora: Profª. Drª. Eliete Maria de Oliveira Caldeira

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Tese defendida em 19 de fevereiro de 2019.

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Programa de Pós-Graduação em Biotecnologia
Ponto Focal Espírito Santo - Universidade Federal do Espírito Santo

DEFESA DE TESE

ALUNO(A): CHRISTIANE MARA GOULART

TÍTULO DO PROJETO: *"UNOBTRUSIVE TECHNIQUE BASED ON INFRARED THERMAL IMAGING FOR EMOTION ANALYSIS IN CHILDREN-WITH-ASD-ROBOT INTERACTION"*

PROFESSOR(A) ORIENTADOR(A): Teodiano Freire Bastos Filho

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Dedico este trabalho a todas as pessoas com Transtorno do Espectro Autista, seus familiares e profissionais da área.

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"What counts in life is not the mere fact that we have lived. It is what difference we have made to the lives of others that will determine the significance of the life we lead."

Nelson Mandela

RESUMO

Emoções são relevantes para as relações sociais, e indivíduos com Transtorno do Espectro Autista (TEA) possuem compreensão e expressão de emoções prejudicadas. Esta tese consiste em estudos sobre a análise de emoções em crianças com desenvolvimento típico e crianças com TEA (idade entre 7 e 12 anos), por meio do imageamento térmico infravermelho (ITIV), uma técnica segura e não obtrusiva (isenta de contato), usada para registrar variações de temperatura em regiões de interesse (RIs) da face, tais como testa, nariz, bochechas, queixo e regiões periorbital e perinasal. Um robô social chamado N-MARIA (Novo-Robô Autônomo Móvel para Interação com Autistas) foi usado como estímulo emocional e mediador de tarefas sociais e pedagógicas. O primeiro estudo avaliou a variação térmica facial para cinco emoções (alegria, tristeza, medo, nojo e surpresa), desencadeadas por estímulos audiovisuais afetivos, em crianças com desenvolvimento típico. O segundo estudo avaliou a variação térmica facial para três emoções (alegria, surpresa e medo), desencadeadas pelo robô social N-MARIA, em crianças com desenvolvimento típico. No terceiro estudo, duas sessões foram realizadas com crianças com TEA, nas quais tarefas sociais e pedagógicas foram avaliadas tendo o robô N-MARIA como ferramenta e mediador da interação com as crianças. Uma análise emocional por variação térmica da face foi possível na segunda sessão, na qual o robô foi o estímulo para desencadear alegria, surpresa ou medo. Além disso, profissionais (professores, terapeuta ocupacional e psicóloga) avaliaram a usabilidade do robô social. Em geral, os resultados mostraram que o ITIV foi uma técnica eficiente para avaliar as emoções por meio de variações térmicas. No primeiro estudo, predominantes decréscimos térmicos foram observados na maioria das RIs, com as maiores variações de emissividade induzidas pelo nojo, felicidade e surpresa, e uma precisão maior que 85% para a classificação das cinco emoções. No segundo estudo, as maiores probabilidades de emoções detectadas pelo sistema de classificação foram para surpresa e alegria, e um aumento significativo de temperatura foi predominante no queixo e nariz. O terceiro estudo realizado com crianças com TEA encontrou aumentos térmicos significativos em todas as RIs e uma classificação com a maior probabilidade para surpresa. N-MARIA foi um estímulo promissor capaz de desencadear emoções positivas em crianças. A interação criança-com-TEA-e-robô foi positiva, com habilidades sociais e tarefas pedagógicas desempenhadas com sucesso pelas crianças. Além disso, a usabilidade do robô avaliada por profissionais alcançou pontuação satisfatória, indicando a N-MARIA como uma potencial ferramenta para terapias.

Palavras-chaves: Transtorno do Espectro Autista. Emoções. Imageamento Térmico Infravermelho. Robô Social

ABSTRACT

Emotions are relevant for the social relationships, and individuals with Autism Spectrum Disorder (ASD) have emotion understanding and expression impaired. This thesis consists of studies about emotion analysis in typically developing children and children with ASD (aged between 7 and 12 years), through infrared thermal imaging (IRTI), a safe and unobtrusive (contact-free) technique, used to record temperature variations in facial regions of interest (ROIs), such as forehead, nose, cheeks, chin, periorbital and perinasal regions. A social robot called N-MARIA (New-Mobile Autonomous Robot for Interaction with Autistics) was used as emotional stimulus and mediator for social and pedagogical tasks. The first study evaluated the facial thermal variations for five emotions (happiness, sadness, fear, disgust and surprise), triggered by affective audio-visual stimuli, in typically developing children. The second study evaluated the facial thermal variation for three emotions (happiness, surprise and fear), triggered by the social robot N-MARIA, in typically developing children. In the third study, two sessions were carried out with children with ASD, in which social and pedagogical tasks were evaluated having the robot N-MARIA as tool and mediator of the interaction with the children. An emotional analysis through facial thermal variation was possible in the second session, in which the robot was the stimulus to trigger happiness, surprise or fear. Moreover, professionals (teachers, occupational therapist and psychologist) evaluated the usability of the social robot. In general, the results showed IRTI as an efficient technique to evaluate emotions through thermal variations. In the first study, predominant thermal decrements were observed in most ROIs, with the highest emissivity variations induced by disgust, happiness and surprise, and an accuracy greater than 85% for the classification of the five emotions. In the second study, the highest probabilities of emotions detected by the classification system were for surprise and happiness, and a significant temperature increase was predominant in the chin and nose. The third study performed with children with ASD found significant thermal increase in all ROIs and a classification with the highest probability for surprise. N-MARIA was a promising stimulus able to trigger positive emotions in children. The child-with-ASD-and-robot interaction was positive, with social skills and pedagogical tasks successfully performed by the children. In addition, the usability of the robot assessed by professionals achieved great score, indicating N-MARIA as a potential tool for therapies.

Keywords: Autism Spectrum Disorder. Emotions. Infrared Thermal Imaging. Social Robot.

CONTENTS

Introduction

Biotechnology and Assistive Technology

Biotechnology is a broad area in which biological processes, organisms, cells or cellular components are exploited to develop new technologies to useful applications in research, agriculture, industry and the clinic (NATURE.COM, 2017). Associated with this definition, several biological signals may be used in studies and works that aim to improve life quality of people in the health and medical fields. Such studies and works also may be included in the Assistive Technology that is becoming more and more targeted in Brazil.

Assistive Technology refers to the devices used to support or replace any impaired function, ranging from simple, low-cost, low-tech gadgets (e.g., button, hooks and reaches) to complex high-tech equipment (e.g., power wheelchairs and computer-aided speech devices) (COOK and HUSSEY, 2002). Assistive Technology also may be defined as an interdisciplinary area of knowledge that encompasses products, resources, methodologies, strategies, practices and services that aim to promote the functionality related to the activity and participation of people with disabilities, inabilities or reduced mobility, aiming at their autonomy, independence, quality of life and social inclusion (BRASIL, 2009). There are many categories of Assistive Technology according to different forms of organization and application (BRASIL, 2009). Basically, these categories comprise (BERSCH, 2013): aids for daily living and practical life; aids to enhance visual ability and resources that increase information to people with low vision or blind; aids for hearing impaired or blind people; architectural designs for accessibility; vehicle adaptations; aids of mobility; orthoses and prostheses; postural adequacy; systems of environmental control; resources of accessibility to computer; aid for sport and leisure; augmentative and alternative communication.

The Assistive Technology Group (NTA – acronym translated from Portuguese: *Núcleo de Tecnologia Assistiva*) at Federal University of Espirito Santo (UFES) encompasses research projects that apply knowledge in robotics, prosthesis, virtual environments, brain-computer interface, smart environments, as well as biological signals, such brain and muscles signals, eye tracking, thermal images, facial expressions, among others, which are aimed for rehabilitation, monitoring and therapies for people with several kinds of disorders (NTA - UFES, 2017).

Context of the thesis

Emotions dictate our behavior and social relations, and their comprehension is much important and increasingly required in current times by the emotional intelligence theme, since this is dependent on the quality of life and the balances of all pillars of the human life (GOLEMAN, 1995; VIEIRA 2017). Therefore, emotions are subjects in multidisciplinary areas of research (neurology, psychology, sociology and computer science) (KROUPI, YAZDANI and EBRAHIMI, 2011).

The understanding of emotions allows people to be able to identify intentions and possible emotions of other individuals (Theory of Mind) and, then, adopt appropriate responses (HAPPÉ, 1994). Individuals with Autism Spectrum Disorder have difficulty interpreting others' emotions, expressing them and communicating (APA, 2013; HAPPÉ, 1994).

Robots have been used for aiding the social and cognitive development of children with ASD (CABIBIHAN et al., 2013; SCASSELLATI, ADMONI and MATARI´C, 2012).

There are several studies about human-machine interaction that discuss the possibility of identification and recognition of emotions by computational systems or robots (PICARD, VYZAS and HEALEY, 2001; PICARD, 2003; SCHEUTZ, SCHERMERHORN and KRAMER, 2006). In this context, this proposed work consists of the unobtrusive analysis of emotions in children with autism spectrum during their interactions with a new social robot as an emotional stimulus, developed at UFES and termed N-MARIA (New-Mobile Autonomous Robot for Interaction with Autistics). In addition to stimulate social skills and record physiological signs of children with ASD, the robot N-MARIA will be evaluated by professionals in relation to its usability as a potential tool of support in therapies.

This study has approval of the Ethics Committee of Federal University of Espirito Santo, under number 1,121,638 (ANNEX A).

Hypothesis

From all aforementioned, the following investigated subjects (hypothesis) of the thesis were formulated:

1. Obtrusive methods have been used to acquire physiological signals in order to identify and recognize emotions, such as electrocardiography (ECG) and electroencephalography (EEG) (VALENZA et al. 2014; NASEHI and POURGHASSEM, 2012). However, they generate discomfort (RUSLI et al. 2016). Individuals with ASD can felt sensitivity to touch (MINSHEW and HOBSON, 2008), making it difficult to perform exams. Thermal camera

is the unobtrusive (contact-free) and efficient sensor to record body thermal variations through infrared thermal imaging (IRTI), which enables the analysis of emotions in children with ASD.

2. Several international works exhibit successful interaction between children with ASD and robots (ROBINS et al. 2010 (a); KIM et al. 2013; WON and ZHONG, 2016; BOCCANFUSO et al. 2017). In addition, our previous studies demonstrated a positive children-with-ASD-robot interaction (VALADÃO et al., 2016; GOULART et al., 2018). The social robot (N-MARIA) is a useful emotional stimulus to trigger emotions in children with ASD and able to record physiological signals for emotion analysis.

Contribution

The contribution of this work is to present a social robot with a thermal camera for emotion analysis in children with ASD. The robot is able to mediate social and pedagogical tasks, be an emotion stimulus and record facial thermal images of children with ASD, in an unobtrusive way, characterizing a great contribution to areas of emotion recognition and social robotics, focusing on its application for ASD field.

Goals

The main goals of this thesis are:

1) Evaluate thermal variations involved in the emotion expressions;

2) Evaluate the robot as an affective stimulus in the interaction with children with ASD;

3) Evaluate social and pedagogical tasks performed by children with ASD during their interaction with the robot in a minimum of two sessions;

4) Assess the social robot as potential tool in therapies, through surveys applied to professionals of this area.

Structure

This thesis approaches the literature review; chapter 1 that addresses the emotion recognition in typically developing children through the variation of the facial emissivity recorded by infrared thermal imaging (IRTI); chapter 2 that discusses an automatic detection method of facial regions of interest (ROIs) for the emotion recognition through IRTI in typically developing children in the interaction with the robot N-MARIA; chapter 3 that describes the evaluation of social skills and pedagogical tasks and the emotional analysis in children with ASD during the interaction with the robot N-MARIA; and general conclusions.

Literature review

Autism Spectrum Disorder

Autism Spectrum Disorder consists of a broad spectrum of clinical manifestations, characterized commonly with a dyad of general symptoms: 1) impairments in reciprocal social communication and interaction; 2) restricted/repetitive patterns of behavior, interests, or activities (WIEGIEL et al., 2010; APA, 2013). Depending on the variety and severity of symptoms, the spectrum can assume mild, moderate or severe / intense levels (APA, 2013).

Considered a neurobehavioral condition, ASD does not have a cure and its occurrence is related to multifactorial conditions in which a genetic factor set and environmental stressors act at particular times during brain development, triggering an autistic phenotype (CASANOVA, 2015). Studies suggest that different genes associated with different brain regions and different cognitive impairments and functional abnormalities can generate the distinct levels of ASD (WIEGIEL et al., 2010). Recently, a burgeoning interest in regards to this condition can be due to the rising prevalence rates of ASD and the concomitant societal, educational, and financial problems (CASANOVA, 2015).

The global average of estimated prevalence of ASD is 62/10,000, according to studies of Elsabbagh et al. (2012), which implies that 1 in 160 children has an Autism Spectrum Disorder, affecting more boys than girls, in a ratio of approximately 4:1 (WHO, 2017; FOMBONNE, 2009). The frequency reported for ASD is of 1% of the world population, and the increase of its rates can be related to an expansion of the diagnostic criteria, increased awareness of the disorder, diagnosis at earlier ages, differences in study methodology, recognition that ASD is a lifelong condition, or, purely, a true rise in its frequency (APA, 2013; MATSON and KOZLOWSKI, 2011; SUN and ALLISON, 2010). In Brazil, it was estimated about 500 thousand people with ASD in 2010 (GOMES et al., 2015), nevertheless there is lack of epidemiological studies able to estimate the exact number and location of people with ASD in the country, in order to establish more effective action policies (MELLO et al., 2013; CANO, 2016). Studies based on prevalence of ASD are important to quantify the increase of the cases of this disorder (MELLO et al., 2013). Some studies of prevalence estimated in other countries can be observed in Table 1. The prevalence rate variation between countries is possibly linked to studies conducted with distinct methodologies, diagnostic procedures and population size (SUN and ALLISON, 2010).

Table 1. Estimated median prevalence in percentage of ASD reported in some countries.

Country	Year	Prevalence (%)	Sample	Source
United States of America	2010	1.5	Children aged 8 years	CHRISTENSEN et al., 2016
Canada	2007	0.6[1] 0.2[2] 0.4[3]	Children and adults[1] Children aged 0-19 years[2]	SSCSAST, 2007

Country	Year	Prevalence (%)	Sample	Source
			Adults[3]	
United Kingdom	1988 to 2001	1.2	Children aged 9-10 years	BAIRD et al., 2006
Norway	-	0.9	Children aged 7-9 years	POSSERUD et al., 2010
China	1987 to 2008	0.1	Children aged 0-18 years	SUN and ALLISON, 2010
Japan	1971 to 2008	0.2	Children aged 0-18 years	SUN and ALLISON, 2010
South Korea	2005 to 2008	2.6	Children aged 7-12 years	KIM et al., 2011

Country	Year	Prevalence (%)	Sample	Source
Venezuela	2005 to 2006	0.2	Children aged 3-9 years	MONTIEL–NAVA, C. and PEÑA, J. A., 2008

Physiological signals and emotions

Physiological patterns originate from the Central Nervous System (CNS) and the Peripheral Nervous System (SNP) (KOELSTRA et al., 2012), and their recognition becomes potentially useful in the evaluation and quantification of stress, anger and other emotions that influence health, and also assumes important applications in medicine, entertainment and human-computer interaction (PICARD et al., 2001).

The emotional state is defined as sets of changes related to neurophysiological and hormonal responses, and facial, body and vocal behaviors, triggered by somatic and/or neurophysiological activity (LEWIS, 2008).

Physiological signals, such as heartbeat, breath, bodily temperature, perspiration, muscle tension, brain signals, pupil diameter, among others, may vary due to impactful events or stimuli, such as harmful event, attack, threat, surprises, and thus, are able to characterize emotional states. When a person is positively or negatively excited, the sympathetic nerves of the Autonomic Nervous System (ANS) are activated, triggering physiologic responses, whose patterns are detectable and inevitable, i.e., are less susceptible to conscious control. In the opposite, speech, gestures or body expressions are responses which may be voluntarily mutable by the humans, masking emotion expressions (PAVLIDIS et al., 2007; NHAN and CHAU, 2010; JERRITTA et al., 2011).

Evolutionarily, in order to ensure the survival of the individual, the physiological responses were and are modulated in response to “fight-or-flight” reactions resulting from stress situations. During such reactions, changes in organ and tissue functions are elicited by the sympathetic system, such as an increase in the delivery of well-oxygenated and nutrient-rich blood to the working skeletal muscles; augmented heart rate and myocardial contractility so that the heart pumps more blood per minute; and stimulation of vascular smooth muscle to trigger widespread vasoconstriction, particularly in the organs of the gastrointestinal system and in the kidneys. The vasoconstriction caused by the sympathetic stimulation redistributes the blood away from these metabolically inactive tissues and towards the contracting muscles, whereas bronchodilation eases the air movement in and out of the lungs to maximize the uptake of oxygen from the atmosphere and the elimination of carbon dioxide from the body. There are an improved rate of breakdown of glycogen into its component glucose molecules (glycogenolysis) and formation of new glucose from noncarbohydrate sources (gluconeogenesis) in the liver that increases the concentration of glucose molecules in the blood. This is necessary for the brain since glucose is the only nutrient molecule that it can use to form metabolic energy. Moreover, there is an enhanced rate of lipolysis in adipose tissue in order to increase the concentration of fatty acid molecules in the blood. Consequently, skeletal muscles consume these fatty acids to form metabolic energy for contraction. Still, the sympathetic system elicits a generalized sweating that enables the thermoregulation during these conditions of increased physical activity and heat production. Lastly, the eyes are adjusted such that the pupil dilates, letting more light in toward the retina (mydriasis) and the lens adapts for distance vision (MCCORRY, 2007).

Throughout human evolution, emotion played an essential role in decisive moments, such as in the orientation of impasses or decision-makings, which are important to be managed solely by the intellect (GOLEMAN, 1995). As recurring challenges were repeated, an emotional repertoire was used to guarantee the survival of the human species, and consequently, this emotional repertoire has been recorded in the human nervous system as innate and automatic inclinations of the heart (GOLEMAN, 1995). Many findings of research from neuroscience and psychology highlight the critical role of emotion in rational and intelligent behavior, then, each type of emotion experienced predisposes the human to an immediate action or signalizes to one direction (PICARD, VYZAS and HEALEY, 2001; GOLEMAN, 1995).

Emotions in social relationships

Emotion is present in all aspects of human life and is a continuous adaptive mechanism related to the purpose of human interaction and expression, as a reaction to stimuli or events (KOELSTRA et al., 2012). Therefore, emotions are a great deal of interest and attention in many areas of research, such as neurology, psychology, sociology and computer science (KROUPI, YAZDANI and EBRAHIMI, 2011). Moreover, studies mention the relevance of emotions in the interpersonal relationships, as potent facilitators of cognitive processes (in decision-makings, for example) and important contributors to many illnesses (stress, for example) (PAVLIDIS et al., 2007). In many aspects of the day-to-day lives, they contribute to communication between humans (NIE et al., 2011).

Emotional states frequently mold social relationships. Thus, understanding them allows people to identify intentions of other individuals, besides adopting appropriate responses. The ability to recognize and label emotions is a social competence that is able to progress since the early childhood to the development of adaptive social behavior. (BAL et al., 2010).

The individuals with ASD have lack of ability to recognize and differentiate emotions in themselves or in the displays of others (HAPPÉ, 1994; RUSLI et al., 2016). This difficulty in the estimation of emotional state of other people may be relative to the cortical impairments in discrimination between stimuli, found in early event-related potential peaks. Such impairments could result from deficits in the early stage of signals perception (YANG et al., 2011). In addition to isolated neural causes, the emotion recognition difficulties are associated with altered attentional, perceptual and cognitive processes, as individuals with ASD process faces differently and show reduced attention to faces and facial expressions. This fact can be due to the mentalistic and emotional information conveyed by the eyes and facial expressions, which may be hard to be read for people with ASD (GOLAN et al., 2010). Many studies have explored emotion recognition in individuals with ASD, taking into account the core deficits in ASD relative to the impairments in reciprocal social interactions and social behaviors (BAL et al., 2010).

Sensors for recording physiological signals

A considerable limitation to current physiological approaches is the need of implantation or direct contact of sensors with the user, with many of them being impractical for most routine user environments (PURI et al., 2005). Sensors able to record physiological signals may be classified, in general, as invasive or non-invasive. Invasive sensors penetrate tissues of interest, in order to eliminate possible interferences in the acquisition of signals from the mechanical barriers composed of layers of skin, tissues or bones and, consequently, to obtain a signal with major quality. However, invasive sensors generate pain and risks to health of individual, with a considerable limitation to the record of physiological signs (PAVLIDIS et al., 2007; MERLA and ROMANI, 2007).

On the other hand, sensors that do not penetrate tissues are classified as non-invasive and are much used in studies in order to record and quantify various types of biological signals. Such non-invasive devices might be intrusive, such as probes, which enter through body openings, generating some discomfort to the patient; or obtrusive, such as ECG (electrocardiogram) electrodes, which are put over the body, i.e., with some physical contact. The non-intrusive or unobtrusive sensors are contact-free. Figure 1 shows common instances of non-invasive devices broadly used in clinical and research areas.

The human physiological information through non-invasive devices has been useful to draw biophysiological inferences about a variety of health symptoms and psychological states, in addition to biometrics, security and surveillance, criminal investigation and human-computer interaction (PAVLIDIS et al., 2007; KHAN, WARD and INGLEBY, 2009). In the literature, numerous works describe physiologic analysis methods that use sensors able to capture such signals in order to evaluate and recognize emotions, as well stress levels, monitor patients in physical rehabilitation who need more frequent healthcare, and detect concealed speech declared by guilty persons during investigations, through the polygraph, for example, popularly known as a lie detector, and others (KREIBIG, 2010; JERRITTA et al., 2011; JOVANOV et al., 2005; POLLINA et al., 2006).

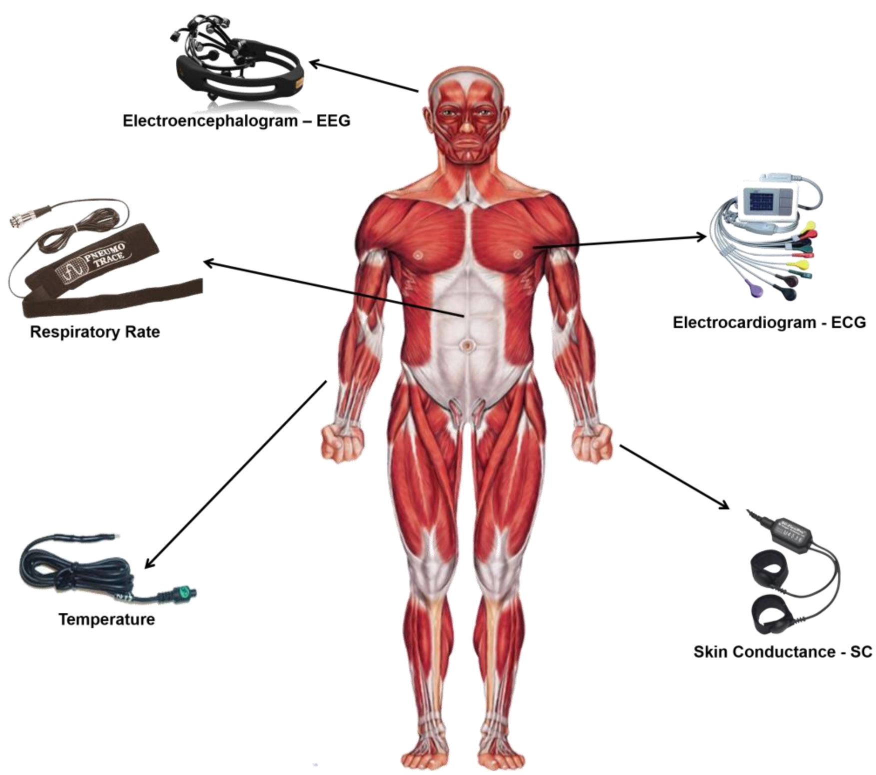

Figure 1. Non-invasive devices and sensors used for physiological signal estimation: brain rhythms (EEG), heart rate (ECG), respiratory rate, temperature, peripheral and skin conductance. Source: Goulart et al. (2014)

Considering the possible sensitivity to touch by individuals with ASD (MINSHEW and HOBSON, 2008), unobtrusive devices may be an useful alternative that enables biological and behavioral analysis for studies relative to the recognition of emotions and common behavior patterns in individuals with ASD. It is worth commenting that there is a paucity of studies evaluating autonomic activity in children with ASD through unobtrusive sensors (BAL et al., 2010).

Thermal camera

The unobtrusive device chosen for our study is the Therm-App®, a low-cost infrared thermal camera able to record body temperature variations. This camera can be attached to Android devices enabling one to display, record, and share infrared thermal images for ‘night vision’ and ‘thermography’ applications. Table 2 exhibits some technical specifications of the thermal device (THERM-APP, 2017).

Table 2. Technical specifications of the Therm-App®.

Weight	138 g
Size	55 x 65 x 40 mm
Minimal requirements	Android 4.1 and above
Resolution	384 x 288 pixels (> 110,000 pixels) 17 µ thermal detector Long Wavelengths Infrared 7.5-14 µm
Range of lens options	6.8 mm (55° x 41°) 13 mm (29° x 22°) 19 mm (19° x 14°) 35 mm (11° x 8°)
Focus	Manual, 0.2 m to infinity
Frame rate	8.7 Hz
Operating temperature	-10 °C to + 50 °C
Accuracy	± 3 ºC
Sensitivity	Noise Equivalent Temperature Difference < 0.07 ºC
Temperature range calibration	5 – 90 ºC
Color palettes	Hot white, hot black, iron, rainbow, grey, vivid

Image processing modes (viewing modes)	Night Vision (optimizes hot object detection) Thermography (provides a clean and accurate basic temperature reading)

Infrared thermal imaging (IRTI) provides recordings of physiological parameters, which are associated with the affective states and indicate the cutaneous temperature, as well as blood flow, cardiac pulse, breathe pattern and skin temperature (RUSLI et al., 2016). Considered an upcoming, promising and ecologically valid method, IRTI has been adopted in a variety of studies involving human emotions (IOANNOU, GALLESE and MERLA, 2014; DI GIACINTO et al., 2014). Thermal image generation is expressed by the following equation:

$$W = \varepsilon \sigma T^4 \quad ,$$

where W is the radiant emittance (W / cm^2); ε is the emissivity (estimated at 0.98–0.99 for human skin); σ is the Stefan–Boltzmann constant (5.6705 x 10^{-12} W / cm^2 K^4); and T is the temperature (K) (SUGIMOTO, YOSHITOMI and TOMITA, 2000).

In addition to being an unobtrusive (contact-free) and highly accurate technique, other advantage of the thermography is the reduction of noises, often evidenced in other physiological measures (NHAN and CHAU, 2009; STEMBERGER, ALLISON and SCHNELL, 2010). In addition, it can be evaluated on both sides of the body, enabling the assessment of asymmetries in temperature and evaluation of larger areas of the skin, not limiting the analysis to the small regions, as with electrodes used in other physiological analysis (RIMM-KAUFMAN and KAGAN, 1996). Moreover, infrared imaging made dynamically may provide a potential physiological access pathway, becoming a powerful tool for inferring psycho-physiological signs, differentiating baseline states of affective states, whereas preserving an ecological and natural context (NHAN and CHAU, 2009; IOANNOU et al., 2013). On the other hand, disadvantages present in thermal imaging consist of artifacts from both environmental effects and metabolic effects of digestion, occlusion of regions of interest (ROI) by eyeglasses or hair bands (STEMBERGER, ALLISON and SCHNELL, 2010).

In corporeal thermoregulation, bodily receptors constantly monitor body and ambient temperatures, in order to maintain the internal body temperature of humans between 36.5 and 37 °C, and they are peripheral (in the skin) or central (in the spinal cord) (GUYTON and HALL, 2006; BRUNO, MELNYK and VÖLCKNER, 2017). Such thermoregulation is performed by temperature regulating centers located in the hypothalamus, through neural feedback mechanisms (GUYTON and HALL, 2006).

Blood vessels are deeply distributed under the skin, and their arrangement can be seen in Figure 2. This arrangement comprises the continuous venous plexus and the arteriovenous anastomoses, which supply blood to the venous plexus and most exposed parts of the body. The conduction of heat to the skin by blood is controlled by the degree of vasoconstriction (cooling) or vasodilatation (warming) of arterioles and arteriovenous anastomoses, basically caused by the inhibition or stimulation of the sympathetic centers in the hypothalamus in response to changes in central body temperature and environment (GUYTON and HALL, 2006).

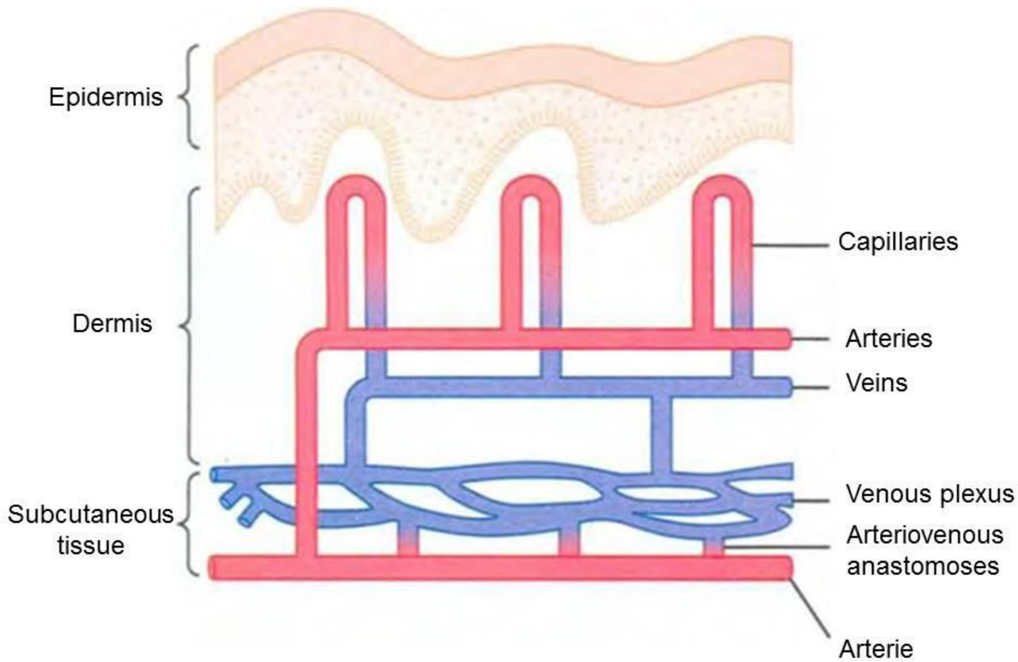

Figure 2. Circulation of the skin. Source: Guyton and Hall (2006).

In fact, the average diameter of blood vessels is around 10.15 µm, very small to be detected by infrared cameras (limited by the spatial resolution); on the other hand, the skin that is directly above blood vessels is on average 0.1 °C warmer than the adjacent skin, beyond the thermal accuracy of current infrared cameras (WU, LIN and XIE, 2008).

Thermal images of the face may provide biometric measurements on human emotions, based on the idea that there are variations of the temperature in various regions of the face according to emotional experience (SALAZAR-LÓPEZ et al., 2015; PAVLIDIS, EBERHARDT and LEVINE, 2002). The human face and body emit both in the mid- (3-5 µm) and far- infrared (8-12 µm) bands, which can be recorded by thermal cameras, producing 2D infrared images (thermograms), enabling sensing temperature variations in the face at a distance (PAVLIDIS, LEVINE and BAUKOL, 2000).

Taking into account that physiological variables, such as superficial blood flow and cardiac pulse, are related in some way to the heat transfer mechanism of the human body (PAVLIDIS et al., 2007), thermography may measure the association between cardiovascular physiology and mental and emotional states reflected in the body (STEMBERGER, ALLISON and SCHNELL, 2010). The response generated by the autonomic nervous system to stress triggers variations in skin temperature, i.e., during an emotional or physical threat, a complex prompting of cutaneous heat variation occurs, involving skin and inner tissues, local vasculature and metabolic activity (SALAZAR-LÓPEZ et al., 2015; IOANNOU et al., 2013). When elevated feelings of alertness, anxiety or fear are experienced by individuals, high levels of adrenaline regulate the blood flow, causing abrupt changes in local skin temperature through redistribution of blood flow in superficial blood vessels, as well as conduction of heat from the blood to the surface of the skin, which is apparent in the human face where the layer of flesh is very thin (STEMBERGER, ALLISON and SCHNELL, 2010; PAVLIDIS; LEVINE and BAUKOL, 2000).

The activation of facial muscles requires blood flow, and the set of branches and sub-branches of vessels that innervate the face muscles evidences the heating of the skin, which may be qualified and quantified by infrared thermal thermography (ZHU, TSIAMYRTZIS and PAVLIDIS, 2007; CRUZ-ALBARRAN et al., 2017). More than twenty muscles comprise the face, and their contractions and relaxations are responsible by the generation of several facial expressions. The set of muscles, arteries and veins that compose the face is shown anatomically in Figures 3, 4 and 5, respectively.

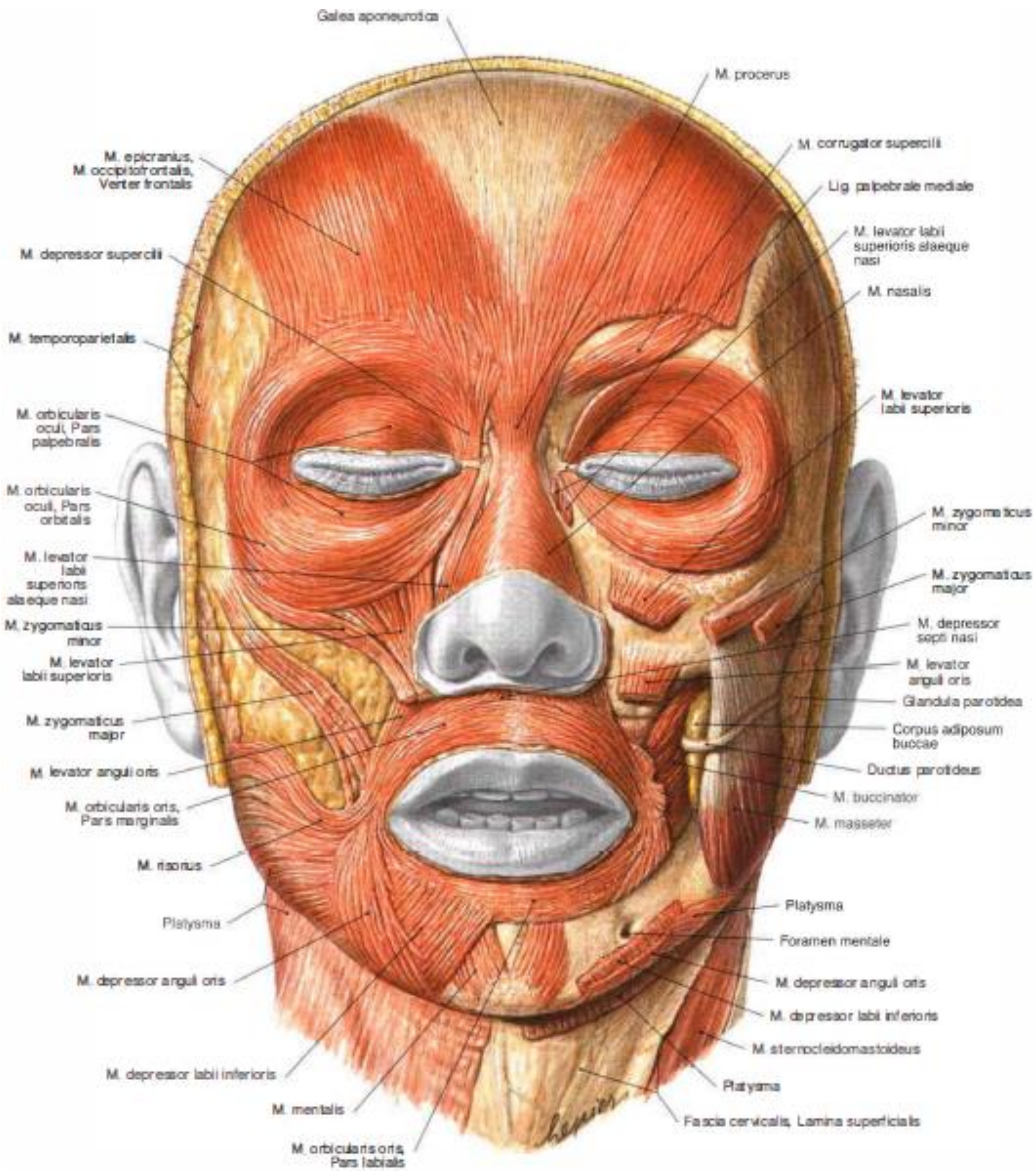

Figure 3. Facial muscles. Source: Putz and Pabst (2006)

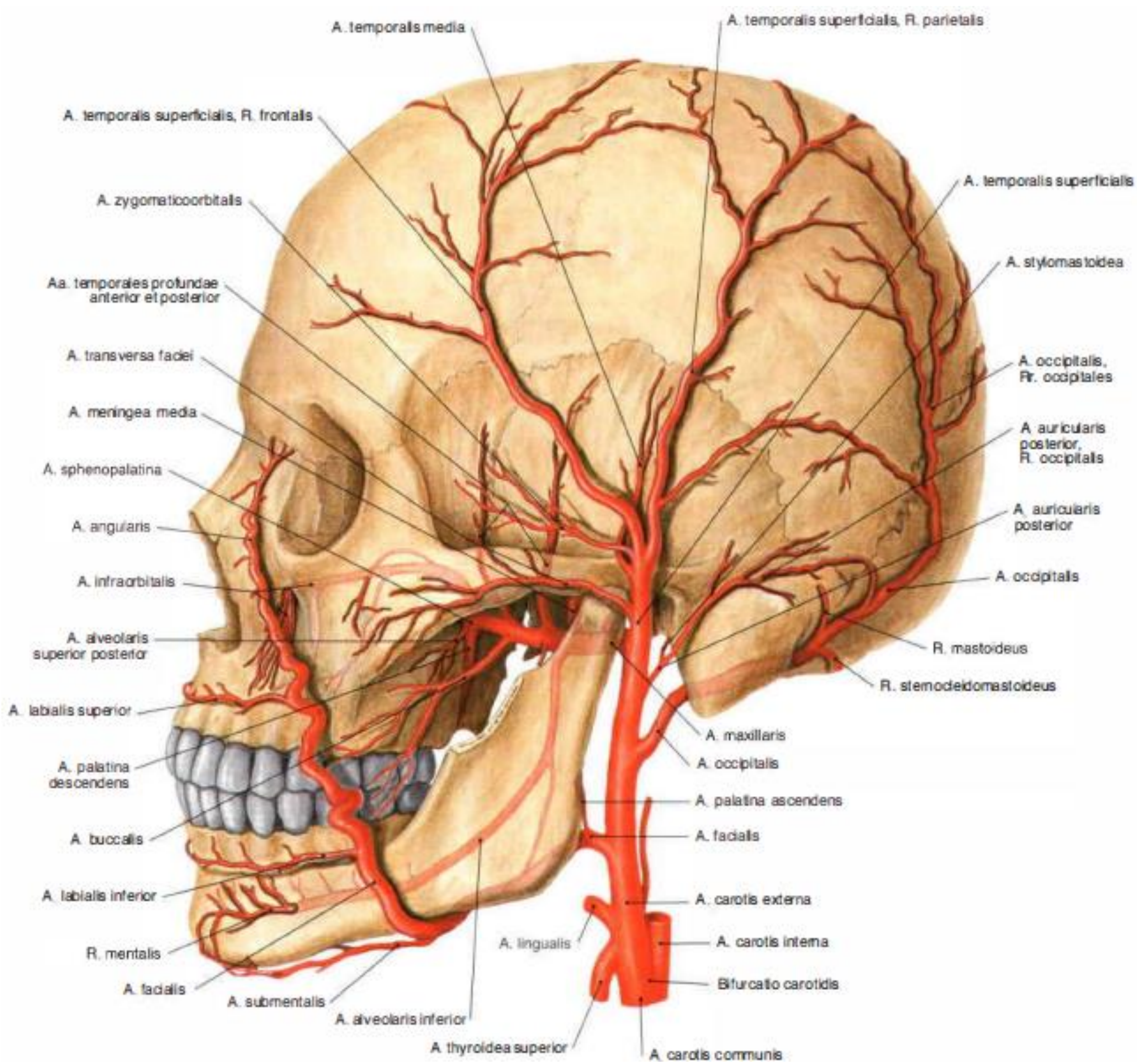

Figure 4. Head arteries. Source: Putz and Pabst (2006)

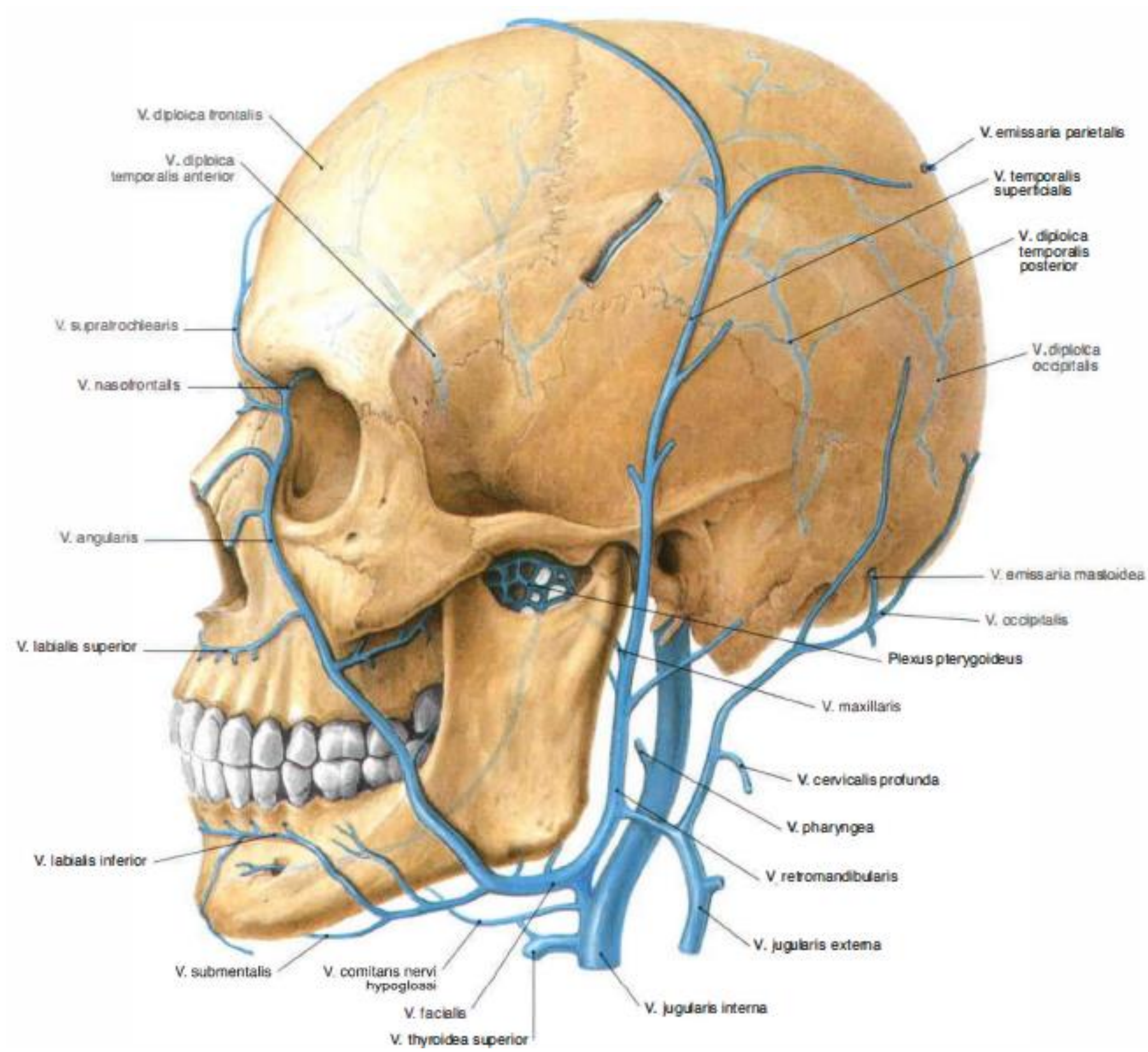

Figure 5. Head veins. Source: Putz and Pabst (2006)

Figure 6 shows the thermal representation for identification of the regions of interest (ROIs) along with a vascular representation of the major vessels affecting the subcutaneous temperature of the face.

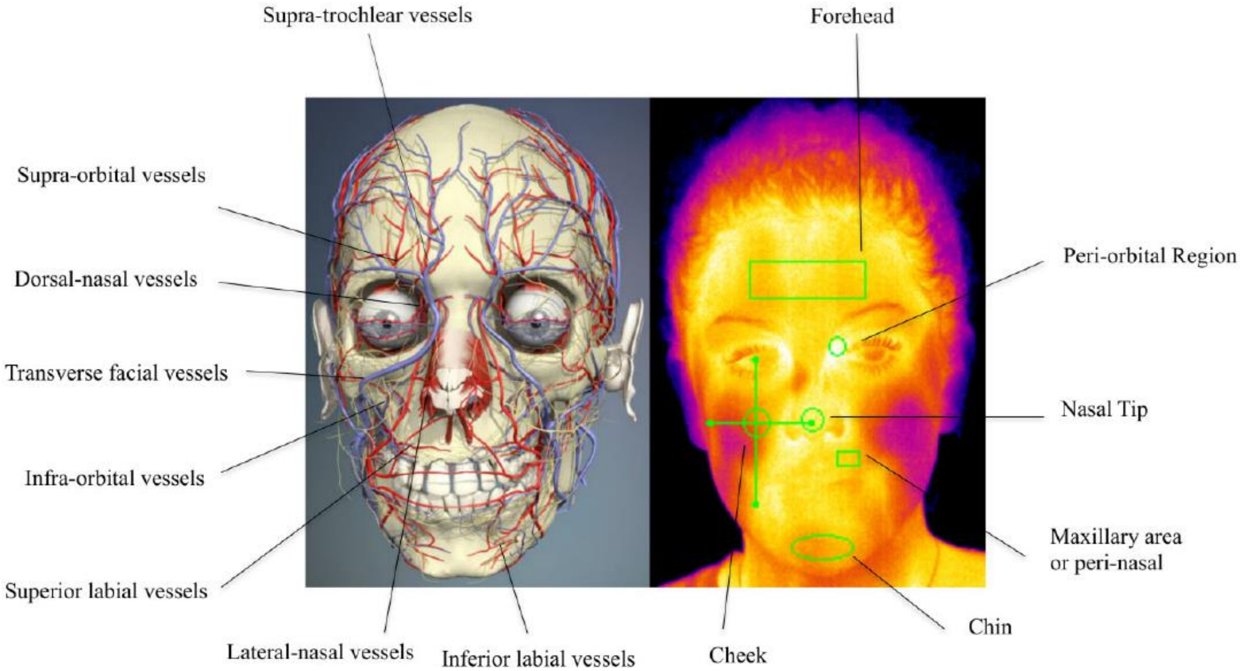

Figure 6. Most common vessels related to facial regions of interest in studies with thermography. Source: Berkovitz et al. (2013) and Ioannou, Gallese and Merla (2014).

Facial expressions are complex muscular patterns resulting from one or more motions or positions of the facial muscles, and their recognition is indispensable before understanding feeling or mental states (JARLIER et al., 2011; SUGIMOTO, YOSHITOMI and TOMITA, 2000). The muscle influence on temperature may be observed in the work of Sugimoto, Yoshitomi and Tomita (2000), where the temperature of the cheek region increased with a high frequency of unconscious (natural) smile performed during a game performance and tended to be maintained or decreased, when the frequency of unconscious smile was low. In contrast, during an artificial smile, there was not an increment of the temperature in the cheek region. Jarlier et al. (2011) examined the relation between the intensity and the speed of muscle contractions and the specificity of the heat pattern produced. They detected a temperature increment in the *zygomaticus* region during a smile (requested action) and a decrease in temperature in the *frontalis* region during the raising of the brows (requested action).

During stress, an increment in blood flow occurs to the forehead region, i.e., the activation of the corrugator muscle requires more blood, drawn from the supraorbital vessels, leading to an increase in temperature in such local (PURI et al., 2005; ZHU, TSIAMYRTZIS and PAVLIDIS, 2007). Moreover, another indicative of stress is the elevated perfusion levels in the periorbital area manifested as higher skin temperatures (PURI et al., 2005).

In thermography, the facial ROIs most studied are forehead, cheeks, periorbital region and nose. Many studies disclose more thermal variations on the nose, being the most reliable region for detecting psychophysiological arousal (IOANNOU et al., 2013). Table 3 mentions some studies relative to facial thermal variations according to emotional states in humans and animals.

Table 3. Facial temperature according to emotional states.

AUTHORS	EXPERIMENTAL SITUATION	EMOTIONAL STATE	SKIN TEMPERATURE (average ΔTemperature (^{o}C))	FACIAL LOCAL
Mizukami et al. (1990)	Simple mother-infant separation Mother is replaced by stranger (in infants aged 2-4 months old)	Mental stress	Decrement (0.3)	Forehead

AUTHORS	EXPERIMENTAL SITUATION	EMOTIONAL STATE	SKIN TEMPERATURE (average ΔTemperature (ºC))	FACIAL LOCAL
Pavlidis, Levine and Baukol (2000)	1) Sound loud noise 2) Gum chewing 3) Leisure walking	Patterns of anxiety, alertness, and/or fearfulness	1) Increment over periorbital area; decrement over the cheeks and increment over the neck (over the carotid) 2)Increment in the chin area 3)Decrement in the nasal area *(Pixel Average Variation Values)	Periorbital area Nasal area Cheeks Chin area Neck area
Levine, Pavlidis and Cooper (2001)	Sudden loud sound	Fear	Decrement Increment	Cheek Around the eye
Pavlidis, Eberhardt and Levine (2002)	Volunteers commit a mock crime and then testify to their innocence	Anxiety	Increment	Eye area
Nakayama et al. (2005)	Monkeys facing a threatening person	Negative emotional states	Decrement (+/- 0.2)	Nose
Nozawa et al. (2006)	Loud and explosive sound	The Fight or Flight reaction (high stress)	Increment (0.18)	Procerus muscle and cheek
Merla and Romani (2007)	1)Electric stimulation 2)Presence of strangers while wrongly performing a	1)Fear to feel pain 2)Embarrassment 3) Sexual arousal	1)Decrement (0.6 ± 0.3) 2) Decrement 3) Increment	1) Face (particularly in the perioral region) 2) Face (particularly in

AUTHORS	EXPERIMENTAL SITUATION	EMOTIONAL STATE	SKIN TEMPERATURE (average ΔTemperature (^{o}C))	FACIAL LOCAL
	stroop test task 3) Watch movies			the perioral region) 3) Periorbital, forehead, mouth, and nose
Zhu,Tsiamyrtzis and Pavlidis (2007)	Lie detection in a mock crime scenario	Anxiety	Increment	Forehead (supraorbital vessels)
Nakanishi and Imai-Matsumura (2008)	Laughter (when a mother plays with an infant)	Pleasant emotion (in infants aged 2-10 months old)	Decrement (between 0.5 and 2.0)	Forehead, cheek and nose (in this, more pronounced decrease)
Kuraoka and Nakamura (2011)	Audiovisual Alone auditory or visual (In monkeys)	Negative emotions (low valence and high arousal)	Decrement (stronger) (0.76, 0.35 and 0.45) Decrement (0.17 for both stimulus)	Nose Nose
Robinson et al. (2012)	Participants received feedback (about their social skills)	Negative and positive emotions	Increment (0.23 0.21 0.28 0.54)	 Brow Eyes Cheeks Mouth
Ioannou et al. (2013)	Toy mishap	Guilt	Decrement (0.05)	Nose
Di Giacinto et al. (2014)	Mild posttraumatic stress disorder (PTSD) patients and control subjects	Fear	Decrement (up to 2.0)	Nose

AUTHORS	EXPERIMENTAL SITUATION	EMOTIONAL STATE	SKIN TEMPERATURE (average ΔTemperature (ºC))	FACIAL LOCAL
	under a sudden acoustic stimulus			
Salazar-López et al. (2015)	IAPS images	Negative valence – low arousal	Decrement (0.85)	Nose
		Negative valence – high arousal	Increment (0.96)	Nose and mouth
		Positive valence – high arousal	Increment (1.66)	Nose, forehead and mouth
		Positive valence – low arousal	Increment (1.01)	General
	Video clips (Contagious laughter condition)	High empathy	Decrement (1.4)	Nose
		Low empathy	Decrement (0.7)	Nose
	Video clip (watching a person suffering pain)	High empathy	Decrement (1.1)	Nose
		Low empathy	Decrement (0.7)	Nose
	Suffering pain	High empathy	Decrement (1.3)	Nose
		Low empathy	Decrement (0.9)	Nose
	Religious video clips + Lord's Prayer and Personal prayers	Love	Decrement (1.1)	Nose
			Increment (1.6)	Face
	Portraits of loved people	Love	Increment (1.5)	Face

Social robots and ASD

Social robots have been designed to interact with humans, evoking social behaviors and perceptions in people with whom they interact (KIM et al., 2013), and thus, increasing more natural and engaged contact. Robots classified as socially assistive focus on assistance based on the social interaction, aiming at automating supervision, coaching, motivation and companionship aspects (TAPUS, MATARI´C and SCASSELLATI, 2007). They aim to establish a relationship with the user that leads toward intended therapeutic goals; provides a benefit to a caregiver by monitoring multiple aspects of the patient and providing ongoing quantitative assessments; in addition to establishing engagement and having the user enjoying interactions with the robot (FEIL-SEIFER and MATARI´C, 2011).

Socially assistive robots can aid several kinds of therapies for individuals affected by stroke, incapacitating aging, dementia, and Autism Spectrum Disorder (ASD) (SCASSELLATI, ADMONI and MATARI´C, 2012; FEIL-SEIFER and MATARI´C, 2011). IROMEC (Interactive Robotic Social Mediators as Companions) is a project that investigates how autonomous and interactive robotic toys can become social mediators by encouraging children with different special needs (autism, mild mental retardation and severe motor impairment) to explore the variety of individual play styles and collaborative games (interaction with colleagues, caregivers, teachers, parents and others) (ROBINS et al., 2010b).

When designed for interaction with children with ASD, these robots might assist therapists and caretakers in the development of cognitive, behavioral and social abilities of these children. Such robots can be promising as an intervention tool, because the interaction between children with ASD and robots is likely positive, as robots tend to be more predictable, simpler and easier to understand than humans (DUQUETTE et al., 2008; ROBINS et al., 2010a). These robots aim to be useful in pedagogical treatments, enabling an optimistic interaction with the children, as well as calling their attention and stimulating them to get contact with the surrounding environment (ROBINS et al., 2010b; SCASSELLATI, ADMONI and MATARI´C, 2012). Studies that investigate the use of socially assistive robots in therapies for ASD usually emphasize specific goals for an ideal human–robot interaction comprising in increased joint attention, eye contact, child initiated interactions, verbal and non-verbal communication, turn-taking, imitative game and overall use of language (BOCCANFUSO et al., 2017). These robots can have several shapes, being classified as anthropomorphic (resemble humans-humanoids), non-anthropomorphic (resemble animals or cartoon like-toys) and non-biomimetic (not resemble any biological species) (CABIBIHAN et al.; 2013).

Anthropomorphic or humanoids robots are used to interact with humans, trying to mimic some human aspects, like playing soccer, dancing, speaking and playing instruments (SCASSELLATI, ADMONI and MATARI´C, 2012; ROBINS et al., 2010b; DUQUETTE, MICHAUD and MERCIER, 2008). Instances of these types of robots are cited below and represented in Figure 7. KASPAR is a humanoid robot that moves its head and arms, articulating gestures to interact with children with ASD, and has touch sensors, which measure the tactile interaction of the child with it (ROBINS et al., 2010a). Another robot is the doll-Robota, which performs a bodily interaction through imitative games using its legs, arms, and head, and is able to stimulate other social interaction skills, such as eye gaze, touch, joint attention, turn taking and communicative competence (BILLARD et al., 2007).

Tito is a humanoid robot composed of wheels, arms, eyes, nose, mouth (for smiling), head (that moves), and hair (that may be illuminated). It emits vocal messages and can sustain autonomous action or be teleoperated by therapists, acting as a mediator in order to stimulate shared attention, physical proximity and imitation of facial expressions and gestures (DUQUETTE, MICHAUD and MERCIER, 2008). CHARLIE (Child-centred Adaptative Robot for Learning in an Interactive Environment) is a low-cost prototype of a small autonomous interactive robot designed to be toy-like for assisted intervention. It has some degrees of movement in hands and heads, and a speaker, which support the performance of interactive games that can be teleoperated by therapists in order to stimulate imitation, shared attention and turn-taking (BOCCANFUSO et al., 2017). Another example of humanoid robot is the Robokind™ Zeno R25, which has a face that displays several reasonably human-like facial expressions in real-time, and a set of sensors and cameras to emit stimuli, to capture behavioral signals of the child and provide him/her with reinforcement. It stimulates eye contact, joint attention, body imitation and facial imitation, promoting basic emotion recognition (PALESTRA et al., 2016). The robot Ono has a face capable of displaying a variety of emotions, touch sensors throughout the body, and verbal ability, to provide support for a therapist in a therapeutic environment (ZUBRYCKI and GRANOSIK, 2016). NAO is a humanoid social robot, well known by institutions and researchers for a variety of applications, including in the field of ASD. With its capability of moving its body (with LED lightening) and verbalizing, it is able to stimulate movement imitation in interactive games, proximity, physical touch, following of instructions, among other applications (LI, JIA and FENG, 2016; SUZUKI and LEE, 2016).

Figure 7. Examples of humanoid robots: a. KASPAR; b. Robota; c. Tito; d. CHARLIE; e. Zeno R25; f. Ono; g. NAO. Source: a. Robins et al. (2010b); b. Billard et al. (2007); Cabibihan et al. (2013); c. Duquette, Michaud and Mercier (2008); d. Boccanfuso et al. (2017); e. Palestra et al. (2016); f. Zubrycki and Granosik (2016); g. Suzuki and Lee (2016).

As examples of non-anthropomorphic robots, PLEO, Paro and KEEPON can be mentioned, which are shown in Figure 8. PLEO consists of a dinosaur-robot designed to express emotions, through body movements and simple vocalizations, triggering verbalization and interaction with another person during games, in which it acts as a mediator (KIM et al., 2013). Paro is a seal robot able to recognize speech and detect sound source direction. It is composed of tactile sensors, mobile parts (neck, paddles and eyelids) and represents facial expressions (happy and sad), besides having four senses: sight, audition, balance and tactile, designed to coexist with people, providing them joy and relaxation through physical interaction (SHIBATA, KAWAGUCHI and WADA, 2012). KEEPON is a little yellow dummy robot, shaped to execute emotional and attention exchange with children with ASD (KOZIMA, NAKAGAWA and YASUDA, 2005), capable of aiding and encouraging them to perform interpersonal communication in a playful way and relaxed mood, stimulating social interactions with robots, peers, and caretakers (KOZIMA, NAKAGAWA and YASUDA, 2005; KOZIMA, MICHALOWSKI and NAKAGAWA, 2009).

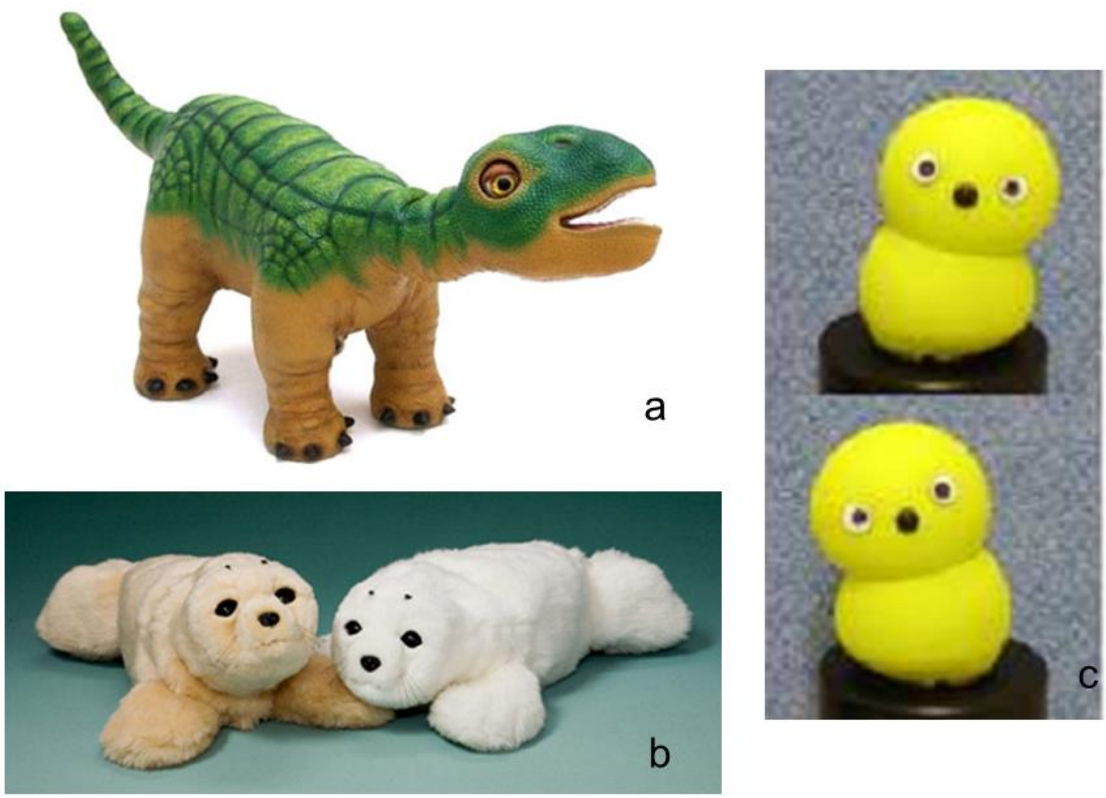

Figure 8. Examples of non-anthropomorphic robots: a. PLEO; b. Paro; c. KEEPON. Source: a. Kim et al. (2013); b. Shibata, Kawaguchi and Wada (2012); c. Kozima, Nakagawa and Yasuda (2005).

Non-biomimetic robots are creature-like robots, for example the robots ROBUS, Roball, Pekee and Labo-1, which are shown in Figure 9. Another common feature among these robots is the mobility. ROBUS (*ROBot Université de Sherbrooke*) is a mobile robotic in which several shapes might be implemented with different functionalities (moving parts, people following and interactive games), aiming to increase the child's attention and to make the environment around her/him more interactive (MICHAUD and CLAVET, 2001). Roball is a spherical mobile robot that has autonomous movements, such as spinning, shaking or pushing, and it is composed of proprioceptive sensors that enable the robot to adapt its behavior, through vocalizations and motions performed in relation to interaction modes with the children (MICHAUD et al., 2007). Pekee is a mobile robot that proposes to engage the children and encourage interaction, stimulating approaching, tactile interaction and shared engagement with the mediator (SALTER, DAUTENHAHN and BOEKHORST, 2006). Labo-1 is a mobile robot used in trials on interactive games with children with ASD, equipped with heat sensors for the detection of the child, and an optional voice generation device to elaborate speech phrases (DAUTENHAHN, 2007).

The locomotion of robots is a good attraction to catch the child’s attention, since children with ASD, especially, tend to be more attracted towards moving things (CABIBIHAN et al., 2013). The mobility of the robot allows many possibilities of ways to interaction with the children (SALTER, DAUTENHAHN and BOEKHORST, 2006; CABIBIHAN et al., 2013).

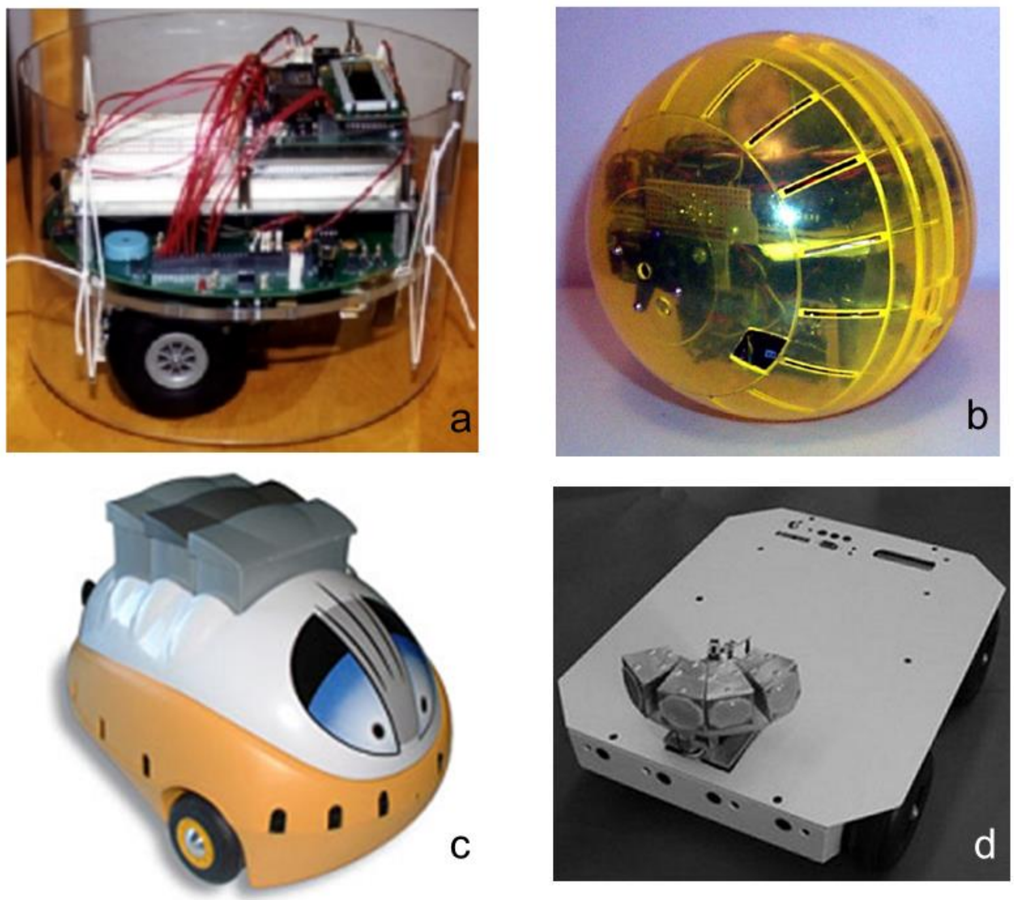

Figure 9. Examples of non-biomimetic robots: a. ROBUS; b. Roball; c. Pekee; d. Labo-1. Source: a. Michaud and Clavet (2001); b. Michaud et al. (2007); c. Cabibihan et al. (2013); Salter, Dautenhahn and Boekhorst (2006); d. Dautenhahn (2007).

With the increasing development of the machine emotional intelligence in robots, these are able to recognize human emotions (PICARD, VYZAS and HEALEY, 2001) and, also, express them. Thus, socially assistive robots might act as social actors, trying to exhibit emotional cues with potential to affect people in the same manner as the emotional expressions of other people do (MATSUMOTO et al., 2015). This point is very interesting to improve the human-robot interaction, making it more natural, and to understand better human emotion and behavior, as those of children with ASD, for instance, since they have difficulty in expressing emotions and they interact well with robots (DUQUETTE, MICHAUD and MARCIER, 2008).

N-MARIA

Several aspects from the aforementioned robots were taken into consideration to the building of the new version of the robot N-MARIA (New-Mobile Autonomous Robot for Interaction with Autistics):

-dynamic face with expressions of six basic emotions (happiness, sadness, anger, disgust, fear and surprise, beyond neutral);

-vocalizations with ready dialogues;

-autonomous movements (locomotion);

-safe and entertaining structure composed of touch sensors and thermal camera.

With these aspects, it is expected that the robot N-MARIA will catch the child's attention easily.

According to the premises that mention that children with ASD prefer predictable, stable environments and have difficulty in understanding facial expressions and other social cues, the aforementioned aspects were carefully researched in the literature to be applied in robot N-MARIA (CABIBIHAN et al., 2013; GIULLIAN et al., 2010; WOODS, 2006; ROBINS et al., 2007; MICHAUD, DUQUETTE and NADEAU, 2003).

To know the children's expectations about robots, in order to aid in the new structure to build the robot N-MARIA, drawings were requested from 187 typically developing children

(78 girls and 109 boys) aged between 6 and 12 years ($\overline{X}$ = 8.4 and SD = 1.43), students of the partner schools of this research, according to their own criteria about shape, functions and contexts of robots.

One hundred eighty seven drawings were made and analyzed considering some physical aspects, based on the research of Woods (2006):

- Appearance (human-machine, animal-machine, machine-like)
- Made of locomotion
- Shape
- Design categories (overall appearance – car, animal, human, machine…)
- Facial features
- Gender
- Functionality (toy, friend, machine)
- Other features: accessories or extra characteristics.

The analysis showed that the majority of the robots designed presented eyes, nose, mouth and teeth with humanoid aspects, seeming to be male gender (24%) and female gender (22%), and the others had undefined gender. 78% of drawings showed humanoid robots under a geometric body (square - 59%), and with legs and feet for locomotion (53%). 75% of the robots were demonstrated as friendly. Examples of some drawings are showed in Figure 10.

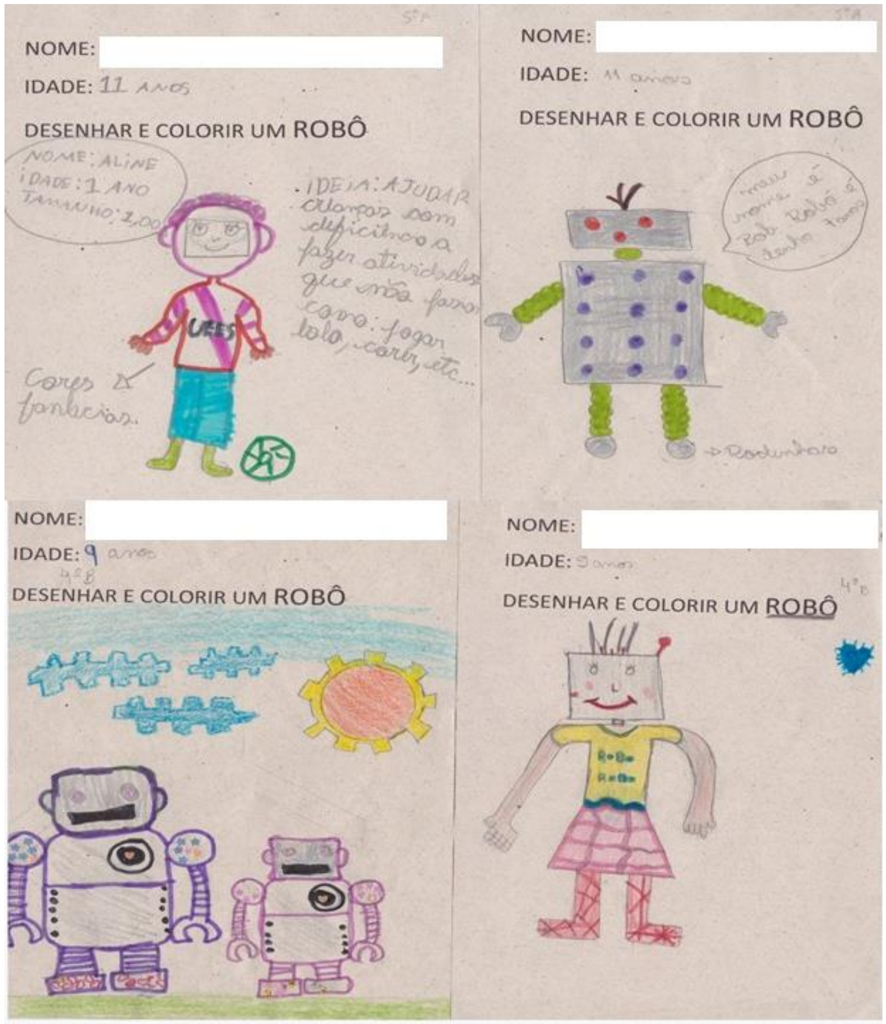

Figure 10. Some examples of robots drawn by children.

According to literature, to make the robot more attractive to the children, it should have a ludic shape, with balanced human-like and mechanical-like features, since if it looks too human, it may lead the children to fear it or not be interested in it, whereas if it looks too mechanical, the child would be more interested in examining it, instead of interacting with it (GIULLIAN et al., 2010; VALADÃO et al., 2016). Moreover, the robot height should be similar to children's height, in order to allow eye-level interaction (VALADÃO et al., 2016).

An important part of the body developed for the N-MARIA robot was the head, composed of a tablet, in which six emotional facial expressions are dynamically displayed, and a Bluetooth speaker. To make the child-robot interaction more entertaining and friendly, the face consists of simple caricatures with eyes that blink, eyelashes, eyebrows, nose and mouth, presenting a color for each expression of emotion, inspired from the film "Inside Out" (name in Portuguese: "*Divertidamente*") (Figure 11). Thus, sad face is blue, disgust is green, angry is red, fear is purple, happy is yellow and surprise is orange. The neutral face is white. When the robot verbalizes, the face becomes neutral and the mouth moves along with pre-programed dialogues. The aforementioned features about the robot's face can increase interest and attention of the child and ensure a natural interaction (LEE, KIM and KANG, 2012).

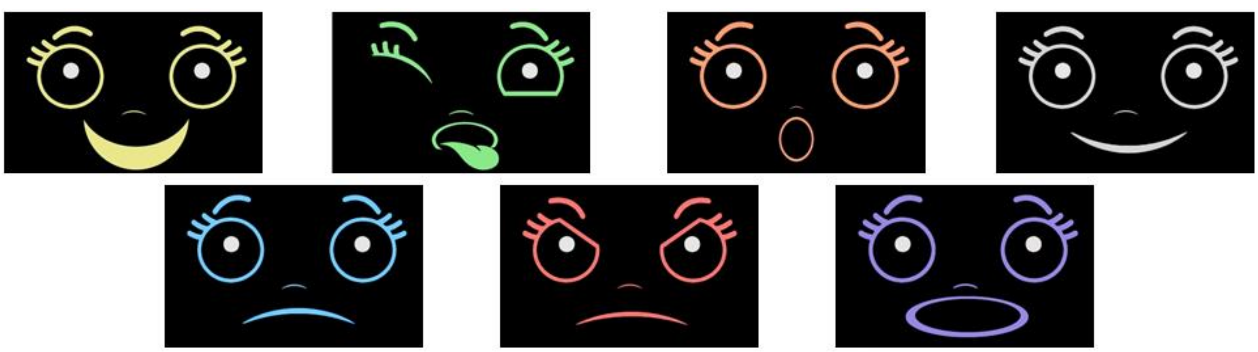

Figure 11. Emotional face expressions of the N-MARIA robot. From left to right, the upper pictures refer to the following feelings: happiness, disgust, surprise and neutral; the lower pictures, sadness, anger and fear.

The facial animation was made using two different software: Piskel, a free software used to elaborate all the images, whose transitions are made in a conjunct of layers, so that animation can be smoothed. The other software is the Unity 3D, which makes possible the creation of animations, triggered by clicks on the screen, and the capacity to import a program written in C# to Android.

Details about the development and assessment of dynamic faces of the N-MARIA can be found in Santos et al. (2017).

N-MARIA has 1.41 m height, near to a typical child's height aged nine-ten years old. Its body was built with soft and malleable materials, such as EVA (Ethylene Vinyl Acetate), foams and fabrics that were molded and are able to protect internal devices and sensors, as well as the children. The mobile platform (Pioneer 3 DX) enables locomotion for the N-MARIA, and a 360° laser sensor (LiDAR - Light Detection and Ranging) allows the child's localization in the environment. Two NUCs (Next Unit Computing*)* control the robot, one for the control of the Pioneer and LiDAR, and another for the acquisition of thermal and RGB images and touch sensors. A tablet displays the facial expressions and the preprogramed dialogues (exhibited through the speaker connected to the tablet via Bluetooth). The energy source for the two NUCs is a 60 Ah battery, placed on the Pionner. The Pioneer, battery and one of NUCs are hidden by a colorful skirt. The N-MARIA, as well as its interior part, can be seen in Figure 12.

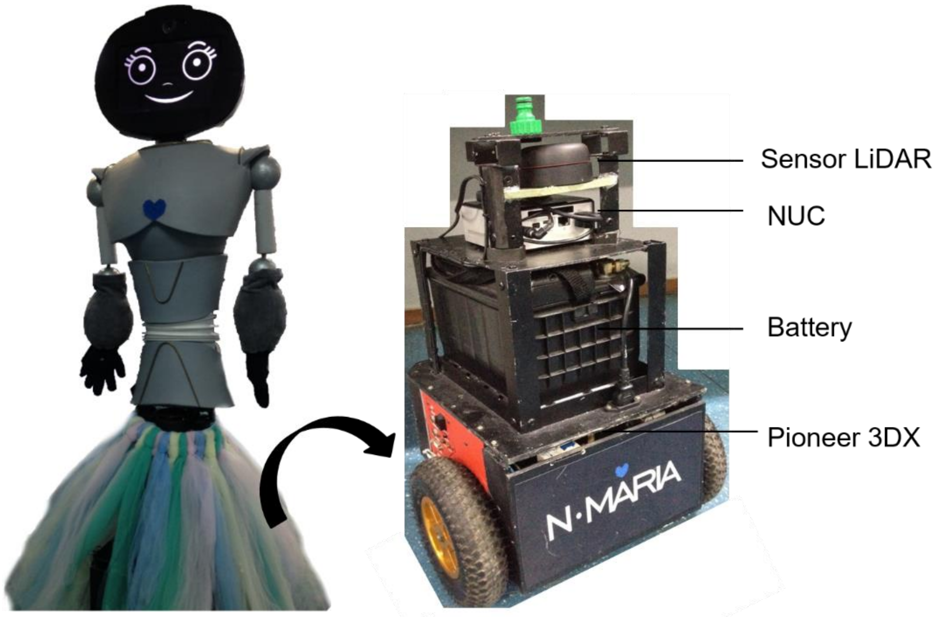

Figure 12. Robot N-MARIA (left) and its inner part (right).

In addition to being able to interact with the child, the robot can be also controlled by the therapist for social pedagogical activities with children, using another tablet. The control of the robot by the therapist is characterized by an interface developed that enables the robot to perform all the preprogramed commands. The interface was designed using C# and Unity languages. A computational server was created to establish the communication between a main NUC and the therapist's tablet. The commands performed by the therapist via tablet are stored and executed instantly. The server is exempt of communication with Internet, since the server is in the physical space of the NUC. The server communication is made through Wireless Local Area Network (WLAN).

Figure 13 shows the graphic user interface (GUI) with some commands installed in the tablet of control.

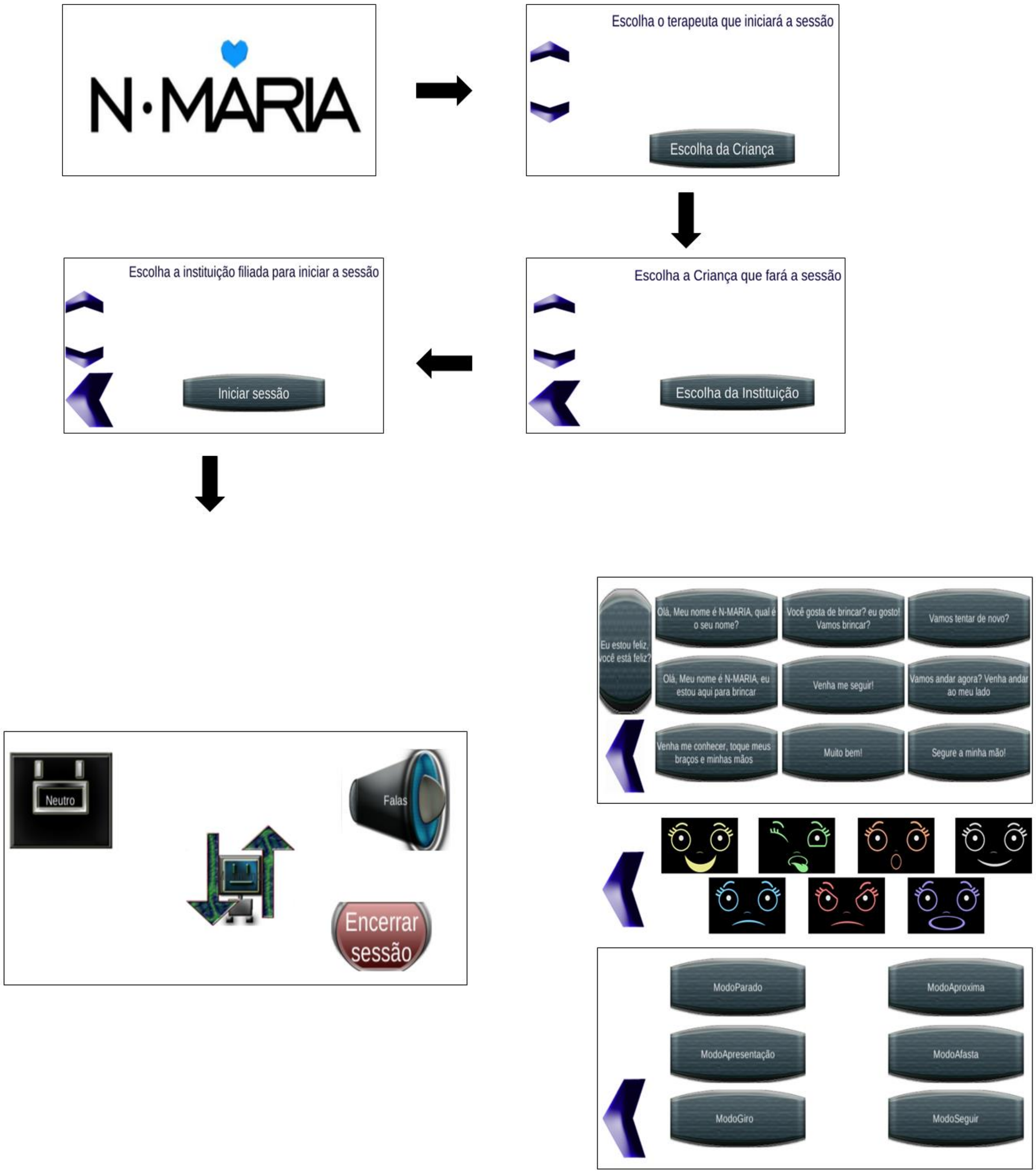

Figure 13. Graphic user interface installed in the tablet for controlling the robot.

Chapter 1

Emotion Analysis in Children through Facial Emissivity of Infrared Thermal Imaging

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Abstract

Physiological signals may be used as objective markers to identify emotions, which play relevant roles in social and daily life. To measure these signals, the use of contact-free techniques, such as Infrared Thermal Imaging (IRTI), is indispensable to individuals who have sensory sensitivity. The goal of this study is to propose an experimental design to analyze five emotions (disgust, fear, happiness, sadness and surprise) from facial thermal images of typically developing (TD) children aged 7-11 years using emissivity variation, as recorded by IRTI. For the emotion analysis, a dataset considered emotional dimensions (valence and arousal), facial bilateral sides and emotion classification accuracy. The results evidence the efficiency of the experimental design with interesting findings, such as the correlation between the valence and the thermal decrement in nose; disgust and happiness as potent triggers of facial emissivity variations; and significant emissivity variations in nose, cheeks and periorbital regions associated with different emotions. Moreover, facial thermal asymmetry was revealed with a distinct thermal tendency in the cheeks, and classification accuracy reached a mean value greater than 85%. From the results, the emissivity variations were an efficient marker to analyze emotions in facial thermal images, and IRTI was confirmed to be an outstanding technique to study

emotions. This study contributes a robust dataset to analyze the emotions of 7-11-year-old TD children, an age range for which there is a gap in the literature.

Keywords: Emissivity Variation. Emotion Analysis. Emotion Classification. Facial Thermal Asymmetry. Infrared Thermal Imaging. Valence.

Introduction

Studies focused on emotions has increased worldwide, mainly due to their importance for the interpersonal relationship field but also as they are considered potent facilitators of cognitive processes and contributors to many illnesses [1]. In many aspects of daily life, emotions frequently mold social relationships, contributing to communication between humans [2] and enabling the identification of a person's intention to adopt appropriate responses [3].

In the emotion analysis field, valence (pleasure) and arousal (intensity) are consistent emotion dimensions for emotional perception, which have shown correlation with physiological signals, such as signals from facial muscle activity, skin conductance, heart rate, startle response and brain waves [4–6]. Moreover, efforts for emotion recognition through physiological markers are evident in many studies that show accuracy varying between 60% and 90% using electrocardiography (ECG) [7], electroencephalography (EEG) [8–10] and thermography signals [11–13].

Human faces play an important role in conforming facial expressions and revealing emotions; they are not totally symmetric, with emotions being more strongly expressed in the left side of the face [14]. Facial expressions are derived from both facial muscle activation and influences of the autonomic responses (pallor, blush, pupil size, sweat), revealing threatening or attractive events experienced by the person [15,16]. The set of branches and sub-branches of vessels that innervate the face demonstrates the heating of the skin, which may be related to emotions and studied through Infrared Thermal Imaging (IRTI) [13,17].

IRTI is an upcoming, promising and ecologically valid technique that has been increasingly adopted in studies involving human emotions, which may be associated with physiological parameters [18–20]. In addition, it is a relevant, contact-free technique for people's comfort without the usage of sensors on the body [21].

Although IRTI has been widely employed in studies with adult subjects for emotion analysis and recognition [12,13,22,23], similar studies in children have rarely been addressed [18,24,25]. To the best of our knowledge, an experimental design for emotion analysis by IRTI applied in typically developing (TD) children aged between 7 and 11 years old has not been addressed to date.

The goal of this work is to propose an experimental design to analyze five emotions (disgust, fear, happiness, sadness and surprise) evoked in 7-11-year-old TD children through facial emissivity changes detected by IRTI. An emotion analysis dataset, relative to emotional dimensions (valence and arousal), facial bilateral regions and emotion classification accuracy, was considered.

Materials and Methods

Participants

This study was approved by the Ethics Committee of the Federal University of Espirito Santo (UFES) (Brazil) under number 1,121,638. Twenty-eight children (12 females and 16 males, age range: 7 – 11 years old, M = 9.46 years old, SD = 1.04 years old) participated in experiments. Eleven percent were between 7 and 8 years old, and eighty-nine percent were between 9 and 11 years old. The recruited children group was defined taking into account the age range mainly corresponding to middle childhood. The children were recruited through cooperation agreements established with three elementary schools of Vitoria from Brazil. The children's teachers cooperated with the selection of children according to our inclusion and exclusion criteria; the former consisted of ages between 7 and 11 years old and absence of traumatic experiences and phobias, and the latter consisted of the occurrence of other neurological disorders that affect the development of the brain, usage of glasses and any medicine.

The parents or legal guardians of the children gave written informed consent in accordance with the Declaration of Helsinki. In addition, the children who wanted to participate in the experiments also gave their written terms of assent.

Recording

For the thermal data acquisition, a Therm-App® infrared thermal imaging camera was used, which has spatial resolution of 384 × 288 ppi, temperature sensitivity < 0.07°C, and frame rate of 8.7 Hz. The image normalization was configured to associate lower temperatures with darker pixels (lower emissivity) and higher temperatures with lighter pixels (higher emissivity) with a pixel intensity rate ranging from 0 to 255.

Stimuli

To evoke emotions in the children, audio-visual stimuli were used, as these are considered the most popular and effective way to elicit emotions [26]. A psychologist supervised the affective video selection, which were obtained from the Internet. Five videos (with duration from 40 to 130 s) were selected to evoke the following five emotions: happiness (funny scenes, compilation of babies laughing), disgust (revolting scenes, such as larvae eaten by humans – beetle larva), fear (tenebrous scenes, with sporadic appearance of haunting – lights out), sadness (compilation of abandoned dogs) and surprise (unexpected scenes, such an animal doing improbable actions, mouse trap survivor – commercial). An additional video with positive emotional content (full movie trailer – Toy Story 3) was also selected to allow better understanding of the experiment.

SAM (Self-Assessment Manikins) [27] was used for affective self-assessment by children for each video; it consists of a point scale from 1 to 9 based on valence (pleasure emotions) and arousal (intensity) dimensions [4,27].

Procedure

The experiments were carried out in the morning, between 7 a.m. to 12 p.m., with room temperature held at 22°C. The experimental procedure was performed as described in Figure 1.

In the test room, the child was invited to sit comfortably, and questions about her/his health condition were asked (How do you feel today? Any pain in the body? Did you take any medicine these days? Did you practice any physical activity this morning?). These questions were asked because the thermal analysis of the face region may be influenced by some symptoms, such as stuffy or runny nose, sneezing, headache and fever, as well as by physiological changes due to activity of the autonomic nervous system [28,29]. In sequence, the tasks of the experiment were briefly explained, and it was asked if the child really would like to participate. Once the answer was confirmed, the child signed the term of assent after reading it together with the examiner. To avoid and eliminate possible interference during the facial thermal image recording, long hair and fringes were tied and held with a clamp, respectively, and jewelry or diadems were removed. In sequence, SAM, the scale of emotion self-assessment, was explained.

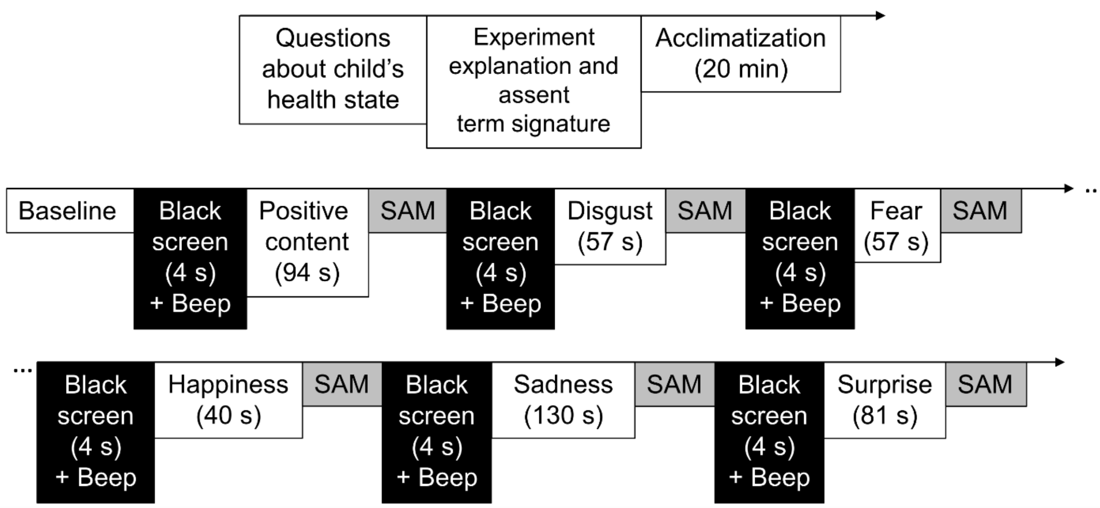

Figure 1. General scheme of the experimental design.

The child was brought into a calm state for at least 20 min in order to adapt her/his body to the room temperature, allowing her/his skin temperature to stabilize for baseline recordings [12,20]. The researcher asked the child not to move and maintain quiet breathing. Meanwhile, brief questions were asked, such as about her/his daily routine, which contributed to the process of relaxation, confidence and proximity to the researcher, with the child becoming more comfortable and less shy or excited during the test.

Next, the child was invited to sit down comfortably on another chair facing a 19-inch screen, with the thermal camera at a distance of approximately 85 cm. The thermal camera was connected to a tablet running Android 4.4.2, in order to acquire the facial thermal images through the Therm-App® application.

The child's head was not kept fixed in a position in order to guarantee the spontaneity of the emotion expression, avoiding any discomfort [29]. However, the child was asked to avoid moving her/his head and putting the hands on the face. In the case of unwanted scenes, she/he was advised to close the eyes, if wished.

The baseline period was recorded before the video display. The affective videos were displayed at the screen to evoke emotions in the following order: positive content video (for training), disgust, fear, happiness, sadness and surprise, according to the psychologist's guidelines of our research group. To avoid the predominance of negative emotions in the child, the psychologist also recommended that the last video exhibition was positive stimuli, in order to positively sensitize children at the end of the experiment (mechanism called empathy) [30].

Both a black screen (displayed for 4 s) and a beep sound preceded each video, whereas SAM was performed after each one. The child indicated which representation of the SAM corresponded to her/his feeling, and, then, the examiner recorded this information. The experiments were individually performed, and the thermal image recording lasted approximately 11 min in total.

Thermal data analysis

Data pre-processing

Figure 2 shows the pre-processing outcomes for a subject who gave written informed consent to publish his thermal images according to the PLOS consent form.

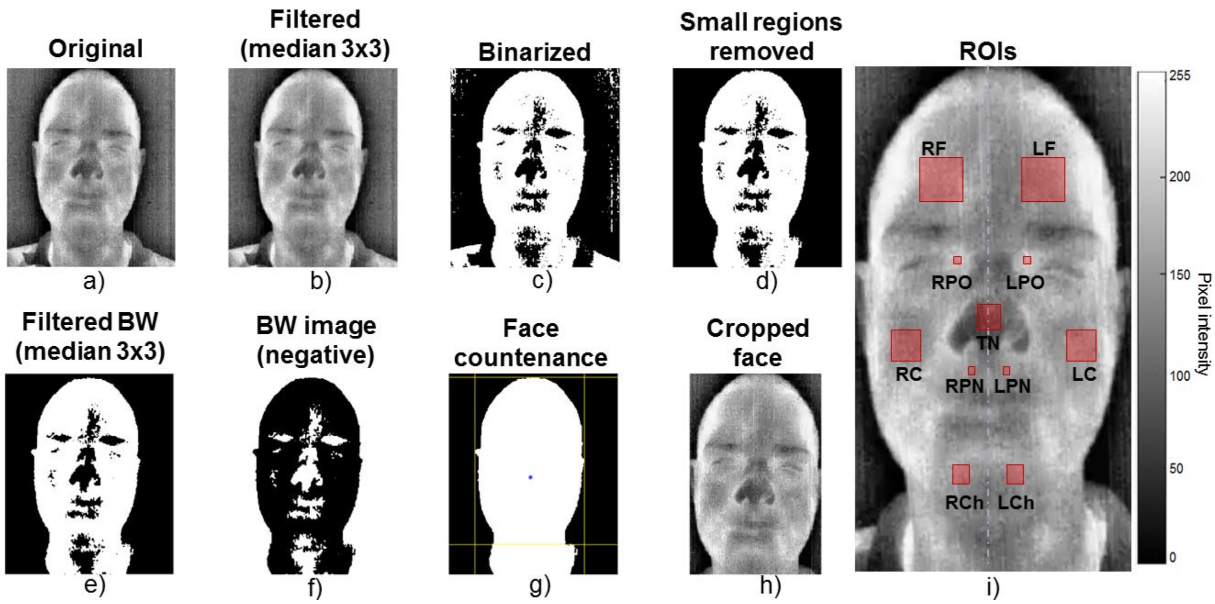

Figure 2. Representation of the pre-processing sequence of the facial thermal images and the eleven regions of interest (ROIs). i) ROIs: LF - forehead (left side); RF - forehead (right side); LPO - left periorbital region; RPO - right periorbital region; TN - tip of nose; LR - left cheek; RC - right cheek; LPN - left perinasal region; RPN - right perinasal region; LCh - chin (left side) and RCh - chin (right side).

The images of the faces were extracted from the thermal images using median and Gaussian filters with further binarization to convert the gray scale image into pure black and white (BW). Small sets of non-connected pixels were deleted to improve image quality, facilitating the foreground identification (face - lighter) and background (darker). Using the BW image, it was possible to detect the face boundaries by finding the uppermost point of the head (the uppermost white pixel), and the left and right limits (the leftmost and rightmost pixels, respectively, near the centroid area). Then, a bottom part of the head was inferred by using a proportional distance from the uppermost head point to the centroid. Eventually, this bounding box was applied to the original image, and the region obtained by cropping into the limits of such area was used to further calculate the statistics.

Forehead, tip of nose, cheeks, chin, periorbital and perinasal regions were the facial regions of interest (ROIs) chosen to extract the affective information, as indicated in [20,31]. Squares were manually positioned on the ROIs of the face in the first frame of each set of the thermal images, enabling an automatic square placement on the subsequent frames of the same video. Then, a visual inspection of the ROI bounds was carried out throughout the recordings to ensure the correct position of the squares on the thermal image.

The bounds of each ROI had fixed proportions (width and height) based on the child's face width [13], such as 6.49% for nose, 14.28% for forehead, 3.24% for periorbital region, 9.74% for cheek, 3.24% for perinasal region, and 5.19% for chin. The ROIs were considered taking into account the bilateral regions of the face in order to analyze the facial thermal symmetry [32,33]. For this purpose, a virtual line symmetrically dividing both sides of the face was used, taking as reference the procerus muscle and the nose. Thus, eleven ROIs were used in our study, as shown in Figure 2i.

Feature extraction

Specific segments of the thermal image recordings were considered and selected for the emotion analysis, per child: 3 s of baseline period (before the audio-visual stimuli exhibition, with the face in neutral state and without emotional stimulus) and 30 s corresponding to each affective video (selection from moments with the highest climax of emotional content and elicitation). During the baseline period, the child was sitting comfortably and relaxed, looking to the camera and not moving.

The thermal images were processed by cropping the ROIs in each frame and further calculating their mean, variance and median values (features), as described below.

Let $\mathbf{R}^k \in \mathbb{R}^{m \times n}$ be the ROI described by several pixels R_{ij} in a range from 0 to 255 (gray scale 8 bits), where k is the current ROI being processed and K the number of ROIs. It is possible to extract from each ROI the feature vector $\mathbf{F}^k = \{f_1, f_2, \ldots, f_{14}\}$, to obtain patterns related to the emotions. The features were extracted from each ROI, as presented in Equation 1.

$$f_1 = \bar{R} = \frac{1}{m \cdot n} \sum_{i=1}^{m} \sum_{j=1}^{n} R_{ij}\,, \qquad (1)$$

where f_1 is the mean emissivity obtained from all pixels R_{ij}, and i and j are the rows and columns of $\mathbf{R}$, respectively.

$$f_2 = \sigma^2 = \frac{1}{(m \cdot n) - 1} \sum_{i=1}^{m} \sum_{j=1}^{n} \left(R_{ij} - \bar{R}\right)^2\,, \qquad (2)$$

where f_2 is the emissivity variance obtained from all pixels.

Similarly, f_3 and f_4 features, which are based on the variance average, were calculated by rows and columns, respectively, as shown in Equations 3 and 4. Here, $\bar{R}_i$ is the mean value of the row i, while $\bar{R}_j$ is the mean value of the each column j.

$$f_3 = \frac{1}{m} \sum_{i=1}^{m} \frac{1}{(n-1)} \sum_{j=1}^{n} \left(R_{ij} - \bar{R}_i\right)^2\,, \qquad (3)$$

$$f_4 = \frac{1}{n}\sum_{j=1}^{n}\frac{1}{(m-1)}\sum_{i=1}^{m}\left(R_{ij} - \bar{R}_j\right)^2 . \quad (4)$$

Additionally, the following features f_5, f_6 and f_7 were computed by the median operator, as shown in Equations 5 to 7, respectively. f_5 is the median value considering all pixels R_{ij} in a unique column vector, while f_6 and f_7 were calculated applying the median operator by rows and columns, respectively.

$$f_5 = median(\mathbf{R}) , \quad (5)$$

$$f_6 = \frac{1}{m}\sum_{i=1}^{m} median(\mathbf{R}_{\mathrm{i}}) , \quad (6)$$

$$f_7 = \frac{1}{n}\sum_{j=1}^{n} median(\mathbf{R}_{\mathrm{j}}). \quad (7)$$

Finally, the previous seven features f_1 to f_7 were used to compute the other seven features by subtracting similar features of consecutive ROIs, as shown in Equation 8, where k is the current ROI being processed.

$$f_{c+7} = \Delta f_c(k) = f_c(k) - f_c(k-1), 2 \leq k \leq K. \quad (8)$$

Then, as each frame has 11 ROIs, and each ROI has 14 features, the total number of features was 154.

Feature selection

For the feature selection, the feature vectors were analyzed according to the training set, searching for those features that minimize the classification errors. Thus, the Neighborhood Component Analysis (NCA) method was used to learn the feature weights using a regularization process [34,35].

Let T={(x_1,y_1), (x_2,y_2)..., (x_i,y_i)..., (x_n,y_n)} be the training set, where N is the number of samples, and x_i is a m-dimensional feature vector with class label $y_i \in$ {1, 2...,C}. The Mahalanobis distance between the points x_i and x_j is given by Equation 9 [34]:

$$d(x_i, x_j) = (x_i - x_j)^T W^T W (x_i - x_j), \tag{9}$$

where W is the transformation matrix, and d is the Mahalanobis distance. If W is a diagonal matrix, Equation 10 can be expressed as follows [35]:

$$d(x_i, x_j) = \sum_{l=1}^{d} \omega_l^2 |(x_{il} - x_{jl})|, \tag{10}$$

where w_l is a weight associated with the lth feature. In particular, each point x_i selects another point x_j as neighbor with probability p_{ij}. Then, a differentiable cost function may be used, which is based on the stochastic ("soft") neighbor assignment in the transformed space, as shown in Equation 14.

$$p_{ij} = \frac{e^{-d(x_i, x_j)}}{\sum_{k \neq i} e^{-d(x_i, x_k)}}, p_{ii} = 0, \tag{11}$$

$$p_i = \sum_j y_{ij} p_{ij}, \tag{12}$$

$$\xi(\mathbf{W}) = \sum_i \sum_j y_i p_{ij} - \lambda \sum_{l=1}^{d} \omega_l^2, \tag{13}$$

$$\frac{\partial \xi(\mathbf{W})}{\partial_{\omega_l}} = 2 \left(\frac{1}{\sigma} \sum_i \left(p_i \sum_{j \neq i} p_{ij} |x_{il} - x_{jl}| - \sum_j y_{ij} p_{ij} |(x_{il} - x_{jl})| \right) - \lambda \right) \omega_l, \tag{14}$$

where p_{ij} is the probability of x_i select x_j as its nearest neighbor; p_i is the probability that the point x_i will be correctly recognized; y_{ij} = 1 for y_i = y_j, and y_{ij} = 0 otherwise; λ is a regularization parameter that can be fitted using cross-validation, and σ is the width of the probability distribution. Let κ = exp(z/σ) be a kernel function with kernel width σ. If $\sigma \to 0$, only the nearest neighbor of the query sample can be selected as its reference point, while to $\sigma \rightarrow \infty$, all of the points have the same chance of being selected apart from the query point. More details can be found in [35].

Emotion classification

The five videos used to evoke the five emotions (disgust, fear, happiness, sadness and surprise) were labeled. For this purpose, segments of 30 s from each video were labeled as having a high potential to trigger the desired emotion. Thus, groups of patterns linked to a same emotion were obtained.

To evaluate the emotion recognition, the training and validation sets were chosen for several runs of cross-validation ($k = 3$). Here, both training and validation sets were formed in each run, selecting only patterns that correspond to the same segment. Afterwards, on each set, 11 ROIs were located on the face to obtain feature vectors (154 features) (see details in Feature extraction section).

The feature vectors of the training set were analyzed through a supervised method for feature selection (of low computational cost) based on NCA [34,35]. Thus, the dimensionality of these feature vectors was reduced, enhancing the class separation and the classification stage. In this instance, the feature vectors of the training set were normalized, using both mean and standard deviation values as reference. Then, the validation set was reduced, taking into account the relevant features, and normalized using the same reference values (mean and standard deviation) obtained from the training set. Finally, Linear Discriminant Analysis (LDA) was used as classifier [36,37].

Statistical analysis

Means and standard deviations were calculated to evaluate the valence and arousal dimensions from SAM. Average values of the emissivity variations were calculated to obtain the mean heat signature in each ROI throughout emotion elicitation, taking as reference the baseline period. Thus, emotion data from the affective videos were compared with data from the baseline. A comparison between the bilateral ROI data of the face was also accomplished to verify the facial thermal asymmetry related to the evoked emotions. Student's *t* test ($\alpha = 0.05$) using a Bonferroni correction was used to verify the significance of such emissivity variations in the facial ROIs. In this study, the data normal distribution was verified applying the Kolmogorov-Smirnov test, rejecting the null hypothesis (normal distribution) at the 5% significance level. For this reason, a logarithmic transformation with base two was applied on the data before applying Student's *t* test. Furthermore, indices such as accuracy, true positive rate (TPR), Kappa and false positive rate (FPR) were used to evaluate the emotion classification.

Results

Valence and arousal analysis

The mean SAM scores for valence and arousal dimensions calculated for the 28 participant children are shown in Table 1.

From Table 1, it is possible to see that the valence scores were pronounced (close to the extreme values of the scale, 1 and 9, corresponding to negative and positive emotions, respectively), whereas arousal scores, close to number five, exhibited a general moderate intensity. Although arousal scores were not substantial, valence scores obtained suggested that the affective videos did trigger specific emotions in TD children.

Table 1. Means and standard deviations (SD) of SAM performed by 28 children.

Disgust		Fear		Happiness		Sadness		Surprise	
Valence	Arousal	Valence	Arousal	Valence	Arousal	Valence	Arousal	Valence	Arousal
Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)
2.64 (1.64)	4.93 (2.69)	2.96 (1.69)	5.71 (3.28)	8.68 (0.82)	5.36 (3.03)	1.68 (1.44)	3.25 (2.69)	7.93 (1.49)	5.68 (3.29)

Thermal data analysis

Feature selection

Figure 3 shows the feature selection frequency from each ROI for each child, considering three cross-validations for the random selection of the affective segments. The tip of the nose was highlighted due to its high feature selection frequency, shown by white squares in Figure 3a.

Figure 4 shows the contribution of each ROI in the feature selection frequency. Seven features were selected: mean, median, variance, mean of the medians on columns, mean of the medians on rows, mean of the variances on columns and mean of the variances on rows. The highest mean values of selection frequency were mean (2.31) and mean of the medians (2.22 and 2.08, for columns and rows, respectively).

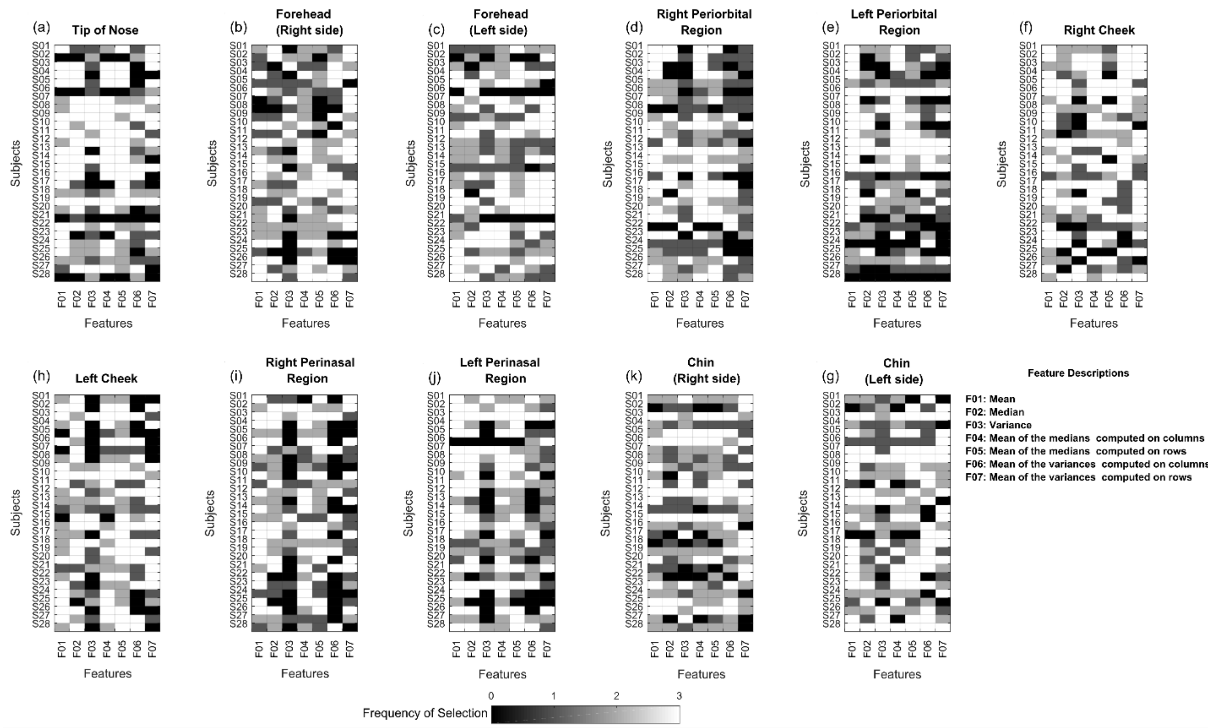

Figure 3. Feature selection maps for each ROI.

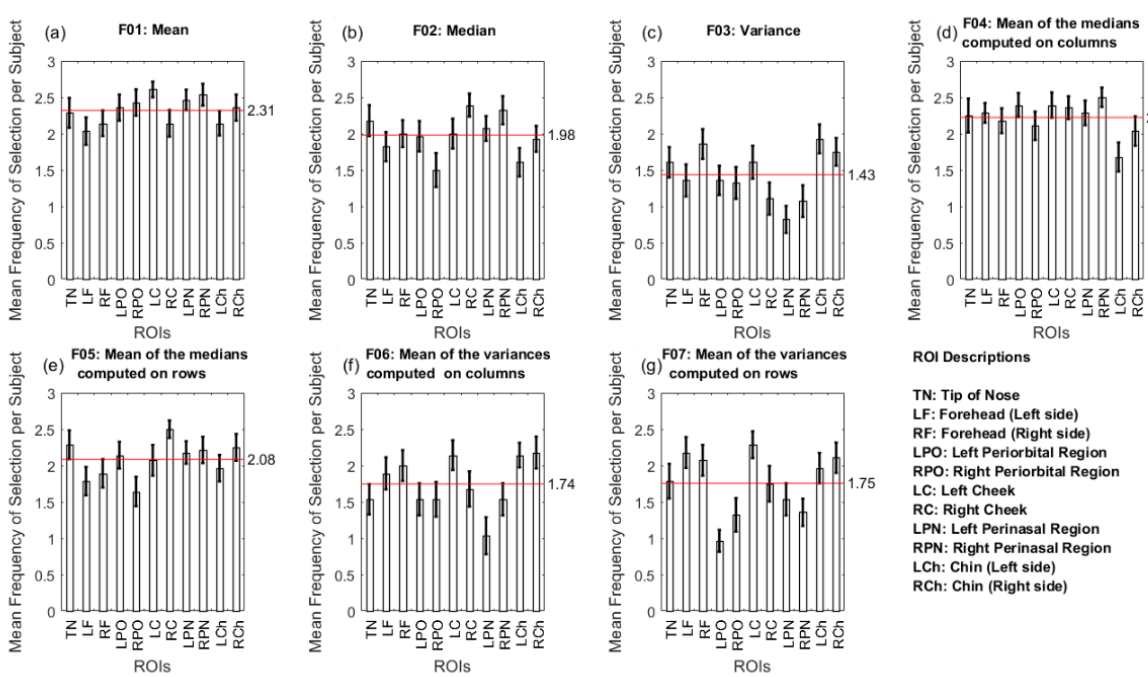

Figure 4. Mean frequency of feature selection per ROIs per subject.

Both Figures 3 and 4 show the independent contribution of the bilateral ROIs for the feature selection, inferring the facial thermal asymmetry.

Emotion classification

The results obtained by the classification for the five emotions had a mean accuracy higher than 85% for the 28 subjects (Figure 5a), with Kappa higher than 81% (Figure 5b). Moreover, the true positive rate was higher than 80% for four emotions, except sadness (Figure 5c). The accuracy reached by the classifier was of 89.88% for disgust, 86.57% for fear, 88.22% for happiness, 74.70% for sadness, and 86.93% for surprise. On the other hand, the false positive rate had a mean value of 3.62% and values lower than 5% for classification errors, with 3.27% for disgust, 4.18% for fear, 4.54% for happiness, 3.50% for sadness and 2.63% for surprise.

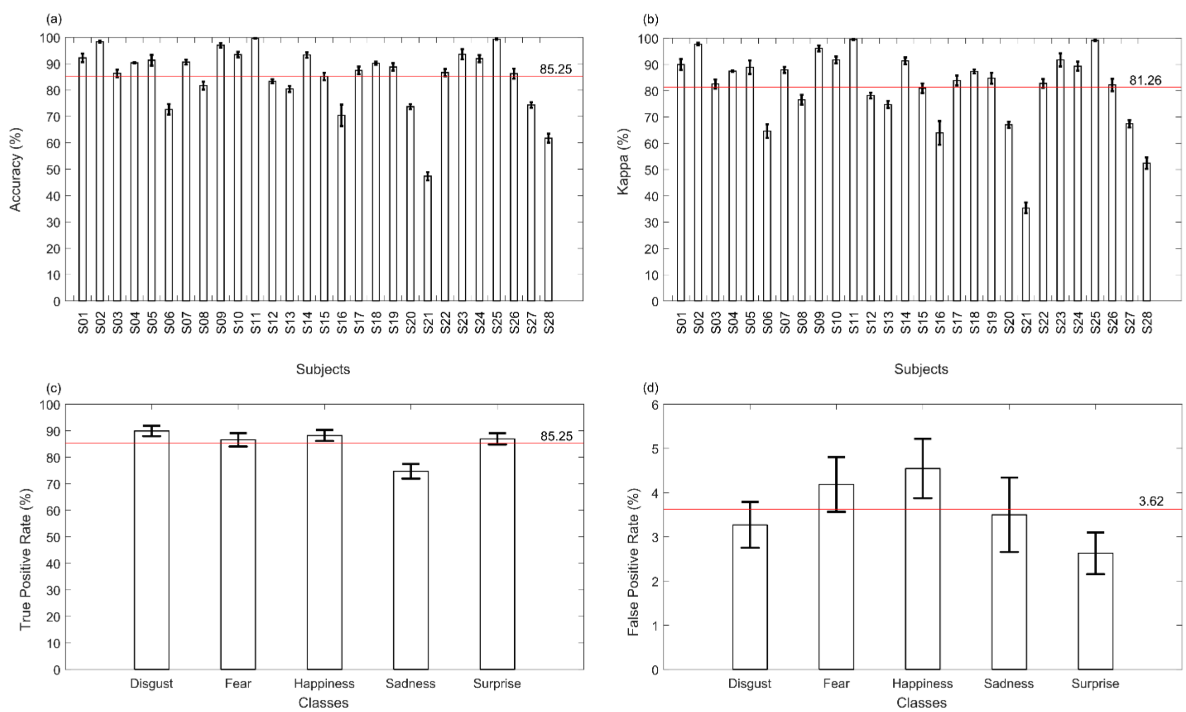

Figure 5. Performance of the emotion classification.

Facial emissivity variation

For the emotion analysis in comparison to the baseline period, the mean emissivity variations were calculated from the eleven ROIs (LF: forehead (left side); RF: forehead (right side); LPO: left periorbital region; RPO: right periorbital region; TN: tip of nose; LR: left cheek; RC: right cheek; LPN: left perinasal region; RPN: right perinasal region; LCh: chin (left side) and RCh: chin (right side)). The pixel values from all ROIs were used for each analyzed frame. Figure 6 shows significant emissivity variations generated by the emotions in the ROIs in relation to the baseline period, considering the thermal tendency (increasing, decreasing or stable). Moreover, Figure 6 shows significant emissivity variations generated by the emotions between the bilateral ROI pairs.

As a result, significant emissivity decreases were observed in the tip of the nose for disgust, fear and happiness, periorbital regions for happiness, sadness and surprise, perinasal regions for disgust and happiness, chin for happiness, sadness and surprise, and forehead for disgust and surprise (Figure 6).

Figure 6 shows significant emissivity variations between all ROI pairs for the five emotions, evidencing the thermal asymmetry of the face. In ROI asymmetry analysis, it is possible to notice the significant variations between the cheek pairs with divergent thermal tendencies (emissivity increases in the left cheek and decreases in the right one) for the five emotions. Moreover, divergent thermal tendencies were observed between periorbital region pairs for disgust and perinasal region pairs for sadness and surprise. Figure 6 also shows a significant variation in the right periorbital region and right cheek, with thermal decreases, and left cheek, with thermal increase, for all emotions.

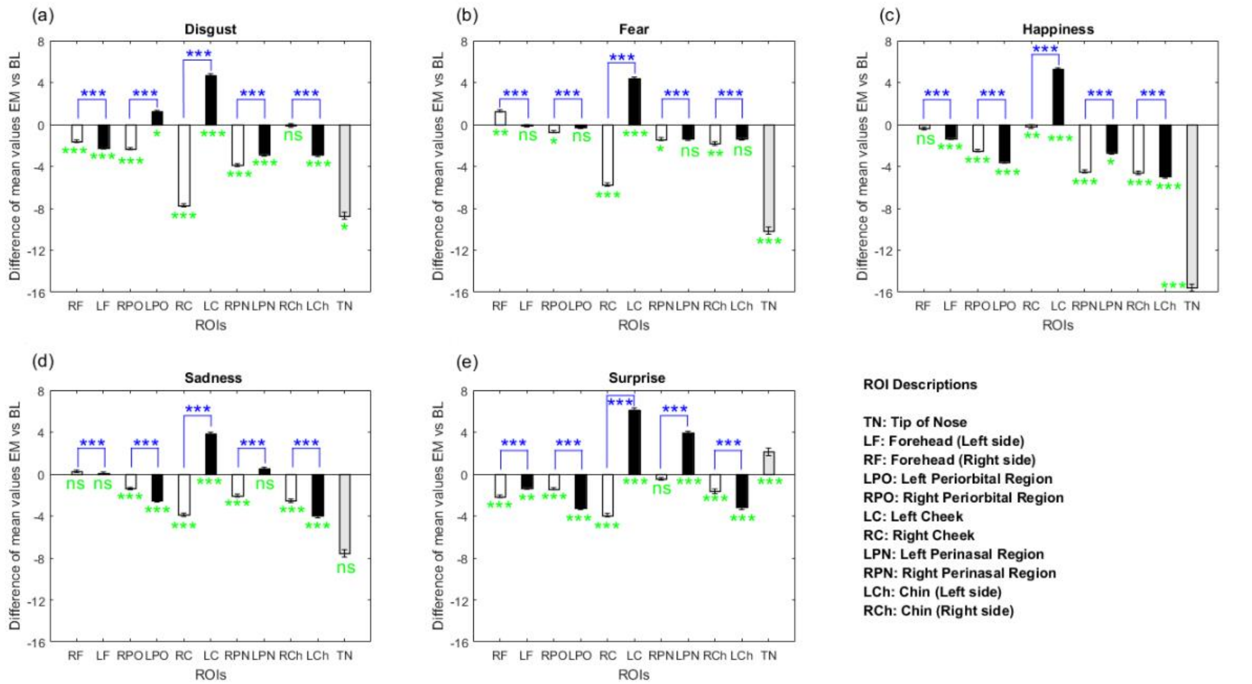

Figure 6. Emissivity variation analysis in the selected ROIs, considering the five emotions, taking as reference the baseline (in green) and the ROI pairs (in blue). The green highlights (below line 0) indicate the significance of emissivity variations in the ROIs triggered by each emotion in relation to the baseline. The blue highlights (above line 0) indicate the significance of emissivity variations occurred between the bilateral ROIs to verify the facial thermal asymmetry. Legend: EM vs BL means Emotion versus Baseline; ns means no significant emissivity variation (*p-value* > 0.05), while * (*p-value* ≤ 0.05), ** (*p-value* ≤ 0.01) and *** (*p-value* ≤ 0.001) indicate significant emissivity variation.

Figure 7 shows emissivity decrease (in relation to baseline) in the nose of a child during the emotions. The child's parents gave written informed consent to publish his thermal images according to the PLOS consent form.

Figure 7. Representative frames of the emissivity decrease (in relation to baseline) in nose of a child during the emotions. Pixel intensity: 0-255.

Discussion

Feature selection and emotion classification

According to Figures 3 and 4, tip of nose, cheeks (especially the right one) and chin (mainly its left side) presented higher contribution of features over all cross-validation. This way, the features' means and mean of medians were highly selected, as shown in Figure 4, with a similar contribution of ROIs located on the right side of the cheeks, left periorbital and perinasal regions.

A growing number of studies aim at an automatic classification of emotions through extraction of information from thermal images [11–13]. The classification method based on LDA used here to recognize five emotions (disgust, fear, happiness, sadness and surprise) reached mean accuracy of 85.25% and Kappa of 81.26%. Specifically, accuracy values of 89.88% for disgust, 88.22% for happiness, 86.93% for surprise, 86.57% for fear and 74.70% for sadness were achieved, confirming the effectiveness of our proposed experimental design.

Regarding the emotion identification and classification through IRTI of other works with adults, our classification performance was similar. For example, in [13], the authors proposed a system that achieved accuracy of 89.90% using another emotion set (anger, happiness, sadness, disgust and fear) with twenty-five adult subjects. In [12], the authors proposed to distinguish between baseline and affective states of twelve adult subjects in (high and low) levels of arousal and valence through visual stimuli (static images). These researchers found an accuracy of approximately 80% between baseline and high arousal and valence levels, while for baseline versus low arousal and valence levels, they obtained accuracy of 75%. In [38], a deep Boltzmann machine (DBM) was used for emotion recognition from thermal infrared facial images through thermal databases of facial expressions, considering 38 adult subjects and evaluating the valence recognition (positive versus negative). They obtained accuracy of 62.9% for classification of negative and positive valence. In [22], a computational model of facial expression recognition of face thermal images was proposed, using eigenfaces to extract features from a face image dataset of only one adult subject, through Principal Component Analysis (PCA). The evaluated emotions were anger, happiness, disgust, sad and neutral, and the proposed system reached accuracy of approximately 97%. In [39], histogram feature extraction and a multiclass Support Vector Machine (SVM) were used as emotional analysis method to classify four emotions (happiness, sadness, anger and fear) from thermal images of 22 subjects available in the Kotani Thermal Facial Expression (KTFE) Database. The authors achieved a classification average accuracy of 81.95%. In [40], the authors used thermal image processing, Neural Network (NN) and Back Propagation (BP) to recognize neutral, happy, surprise and sad facial expressions of one female, obtaining a mean accuracy of 90%.

Valence and arousal analysis and ROIs

The valence dimension represents the state between unhappiness and happiness, whereas arousal is the state between relaxation and activation [41]. In our study, the valence values were pronounced towards the extremities (1 and 9) of the SAM rating (Table 1). Figure 6 showed that happiness, surprise and disgust were the inducers of the greatest emissivity variations in the children's faces, in relation to the baseline. Such emotions triggered significant emissivity variations in pairs of the periorbital region and cheeks and nose. In general, the ROIs that had more significant emissivity variations were the cheeks, periorbital regions and nose.

Some studies highlighted the association between thermal variation in the face and emotional dimensions (valence and arousal), such as in [32]. The authors reported higher correlation between facial thermal changes and arousal than valence, with stimuli obtained from a picture database. In fact, many findings on thermal variations note temperature changes for high arousal settings, mainly associated with high anxiety levels [17,25,42].

In literature, for valence dimension, temperature increments in brows, cheeks and around the eyes were observed in adults, with brows and cheeks related to negative valence and eyes related to positive valence [16]. On the other hand, temperature decrements in forehead, cheek and nose were evidenced in babies, along with pleasant emotions [24]. The work described in [43] evaluates the thermal variation in the perinasal region, considering facial expressions, in order to distinguish examples of negative (unpleasant) and positive (pleasant) arousal, distress and eustress conditions, respectively. For eustress (with positive facial expressions), they found locally elevated perinasal signal, whereas for distress (with negative facial expressions), they found fluctuating perinasal signal. The observed differences can be related to the muscle deformation presented during the facial expression, beyond perspiration (found in distress conditions). Therefore, valence effects could be related to muscular deformations due to facial expressions.

In general, for valence, decreased facial temperature is considered a sign of negative emotions [24], which is confirmed in Figure 6. This predominant decrease observed in most ROIs may be either the reflex of the subcutaneous vasoconstriction under the control of a sympathetic activation mediating the central activation [15,20] or perspiration, a physiological phenomenon from the sympathetic autonomous system, which occurs due to the absorption of the latent heat by perspiration pore activation, decreasing the local thermal emission [44]. Such decreases were detected in the ROI pair of the forehead region during disgust and surprise; the periorbital region during happiness, sadness and surprise; the perinasal region during disgust and happiness; the chin during surprise, happiness and sadness; and finally, the nose during disgust, fear and happiness. On the other hand, forehead was the ROI that had the least variation of emissivity compared to other ROIs. The tendency towards no significant changes in the forehead is consistent with the fact that it has the most stable temperature [20,32]. In general, emissivity decreases were mainly found in the right cheek and right side of the periorbital and perinasal regions for negative emotions (disgust, fear and sadness), and in the periorbital region and chin for positive emotions (happiness and surprise). Decreases in the right cheek and increases in the left cheek were observed for all emotions.

For negative (disgust and fear) and positive (happiness) emotions, a significant emissivity decrement in the nose was particularly noticed (see Figure 6 and Figure 7), in accordance with findings in the literature that indicate nasal temperature decreases during stress, startle and happiness situations [13,15,20]. Thus, it is possible to suppose the contribution of the valence dimension to the nasal thermal decrement. On the other hand, an emissivity increase occurred in the nose for surprise, such as shown in Figure 6. During the surprise video, a fright moment occurred, which may have caused a momentary increment in the heart rate, generating a temperature increase in the face and triggering a vasodilation in the region of the nose [31].

The nose is the most consistent indicator of stress and negative emotions [15,31], presenting solid results, as it is not considered to be greatly affected by expressions. In fact, it is affected by sympathetic responses, such as subcutaneous vasoconstriction or perspiration, which trigger thermal decrements [15,20,44]. Decrease in nasal temperature was observed in distress signs during the investigation of guilt in children with ages between 39 and 42 months [18], and in mild posttraumatic stress disorder subjects exposed to a sudden acoustic stimulus in a fear conditioning perspective [19]. Moreover, many authors consider the nasal temperature as an indicator of affective states in animals [20]. For example, in fear contexts, temperature drops were detected in the noses of monkeys submitted to settings with a threatening person [45], as well as in monkeys exposed to negative audiovisual, with only audio or visual stimuli [46].

Figure 3 reveals the high contribution of the nose in relation to other ROIs for the feature selection frequency. In fact, nose (tip of nose) is an important and much-studied marker for investigation of thermal variations in the face of humans and animals, specifically in distress and fear contexts [15,18,19,45,46].

Bilateral facial thermal variation

The facial asymmetry is easily revealed in the emotional expressions [14], and a thermal difference greater than 0.5 °C might indicate clinical thermal asymmetry [33]. Figure 6 demonstrated significant emissivity differences between all the ROI pairs, inferring thermal asymmetry triggered by emotions. Moreover, a thermal tendency difference in cheeks was observed, with a general thermal decrease on the right side and an increase on the left one. Although there was a significant decreasing thermal tendency for most ROIs, significant emissivity increases were presented in the left cheek and perinasal region for surprise, and in the left cheek and periorbital region for disgust. Moreover, Figure 4 showed the relevance of some bilateral ROIs for the feature selection, presented by the cheek pair, for example.

The asymmetry of the face might be related to the brain lateralization, in which the right hemisphere plays a dominant role in emotion processing [14,47,48]. There is a dominance of the facial left side for emotion expressions, due to its innervation by the right hemisphere, which is dominant for facial emotional expression [49]

Study limitations

The focus of this work was the emotion analysis by IRTI elicited in typical children of developmental ages, for which there is a gap in the literature. Our method presents some limitations, and one is related to the absence of an automated ROI tracking and positioning method. In our work, manual ROI positioning was performed in the first frame of each thermal video, which was used as a reference for the next ROI marking, being automatically propagated to the rest of the video. This was made to ensure the correct positioning of the ROIs. The advantage of using a manual check method is to discard ROIs that are not positioned correctly, assuring an appropriate selection of frames for our analyses. Automatic positioning of ROIs and their tracking methods are subjects for future works, as real-time face tracking could reduce the frame discarding due to ROI positional error or head movements. It could also ensure a correct ROI positioning even during such movements. An example of a facial tracking method could be the combination of particle filtering with a probabilistic template algorithm (spatiotemporal smoothing template) proposed in [50], which enables a fast, flexible and accurate tracker in spite of head movements and physiological changes.

Another limitation of our work is the possible presence of combinations of ROI positional and muscle deformation errors due to facial expressions, which may have produced some of the effects found in our results, as such emissivity decrease in the right cheek and increase in the left one. This facial expression variability due to muscle deformation can affect the thermal variations, and a potential investigation could associate automated methods of both thermal and visual imagery analysis for the recognition of such expressions, as cited in [51], as the fusion of both methods allows a better accuracy compared to the individual modalities.

The fixed size rectangles of the ROIs are also considerable limitations. For example, the size of the periorbital ROI is tiny, and even a few pixels of motion error could affect the statistics. In addition, given that the face covers the entire frame, even a small face motion in actual space may translate to a potential shift in the image plane.

Another limitation is related to the recruited children's developmental ages, between 7 and 11 years old. This age range is large from the developmental point of view; a 7-year-old child is very different from an 11-year-old child in terms of emotional maturity, for instance. In future analyses, a tighter age range (7-8 or 10-11 years old, for example) could be considered. In fact, neuroscience studies have suggested that social and emotional learning is best prior to 6 years of age (early childhood), contributing to future emotional competence and emotion knowledge of children [30]. Despite developmental differences, our sample of children was defined taking into account the age range mainly corresponding to middle childhood.

Finally, the experimental sessions of our study were not counterbalanced, which also characterizes a limitation. Future studies should display the emotional videos in another order to verify the best sequence of stimuli to generate a greater differentiation between the emotions. In spite of this limitation, the psychologist of our research group approved the display order addressed in our work, which was performed for all children in the experiments.

Final considerations

The proposed experimental design was carried out in a careful way with typically developing children aged between 7 and 11 years, in which five emotions (disgust, fear, happiness, sadness and surprise) were evoked by audio-visual stimuli, triggering significant facial emissivity variations in 11 facial ROIs, as recorded using IRTI. An analysis set of emotions considered emotional dimensions, facial bilateral ROIs and emotion classification. To the best of our knowledge, to date, there is no similar experimental design applied in children of this age group in literature.

The emissivity variation analysis through IRTI was demonstrated to be efficient, indicating significant variations in facial ROIs. This can note the ROIs and emotions that deserve attention in future studies with children, which may be more assertive in identifying quantitative patterns for emotion recognition. In addition, IRTI showed to be a valuable touchless technique for emotion analysis.

Our main findings reflect the efficiency of the proposed experimental design and become part of an important data set for support in future work. The main findings were the following: a) mean and means of medians (on columns and rows) were the features with the highest average values for the selection frequency; b) tip of nose, cheeks and chin were the most contributing ROIs for the feature selection; c) a high accuracy (higher than 85%) was obtained for the classification of the five emotions; d) SAM showed valence with pronounced values, with a predominant thermal decrease observed in almost all ROIs in relation to the baseline; e) disgust, happiness and surprise induced the greatest significant emissivity variations in the children’s face; f) thermal decrease in the tip of the nose indicated its relevance as a potential marker for affective states, including for valence; g) cheeks presented significant variations for all emotions; and h) a facial thermal asymmetry was evidenced through distinct significant variations between all the bilateral pairs, with predominant thermal trend differences in cheeks.

Further validation of the results in a larger sample of children is necessary, which is challenging, due to their spontaneous behavior. Therefore, appropriate planning and careful execution of the experimental design is important, in order to extract the most believable information from children.

The experimental design carried out here provided interesting and promising results, generating a robust dataset that can be useful for future studies about emotions and behaviors of children.

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Chapter 2

System based on Viola-Jones for Emotion Analysis and Recognition through Infrared Thermal Imaging: Towards a Social Robot for Children

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Abstract

Human-robot interaction (HRI) has become increasingly addressed in research and applications. This work presents an automatic detection method of facial regions of interest (ROIs) for emotion analysis, based on Viola-Jones. This method includes the recording of facial images by RGB (red, green and blue) camera and infrared thermal imaging (IRTI); Viola-Jones with and without facial ROI repositioning; feature extraction; reduction of feature vector dimensionality through PCA (Principal Component Analysis); classification and analysis of emotions. The emotion analysis is performed using temperature variation (by brightness variation) in typically developing children's faces, through IRTI, when children saw the robot for the first time. The RGB camera is used to detect the ROIs using the Viola-Jones algorithm. Those ROIs are transferred to the thermal camera plane through a homography matrix. A comparison between a method based on Viola-Jones to position ROIs on thermal images and another method to reposition the ROIs (based on the correct manual positioning) shows the distance errors were lower in the method that considers the ROI repositioning. Results also show a significant increase of brightness in nose and chin after children see the robot, with the probability of happiness and surprise being the emotions felt.

Keywords: Viola-Jones. Emotion Recognition. Face Detection. Infrared Thermal Imaging. Socially Assistive Robot.

Introduction

Human-Robot Interaction (HRI) is a growing field in several sectors of life, such as rehabilitation [1], mobility [2], entertainment [3], service [4] and others [5]. Social robots have been applied within HRI to improve interaction with humans, evoking social behaviors and perceptions in people with whom they interact [6], and thus, increasing and making contact more natural and engaged [7,8].

Socially assistive robots are focused on assistance providing the social interaction, aiming at automating supervision, coaching, motivation and companionship aspects [9]. Therefore, they can be useful in elderly care, education, rehabilitation, in addition to aiding with several kinds of therapies for individuals affected by stroke, incapacitating senescence, dementia, and Autism Spectrum Disorder (ASD) [10–12]. The interest in human emotion identification and its association with physiological expressions has encouraged the design and building of robots and systems able to perceive human affective states through physiological signals [13–15].

The face is an expressive means in face-to-face communication, and its expressions enable demonstration of the emotional state, cognitive activity, intention, personality and temperament, truthfulness and psychopathology of a person [16,17]. Facial muscle activations in addition to autonomic responses (such as sweat, pallor, blush and pupil size) collaborate in the formulation of emotional facial expressions [18,19]. However, facial expressions as well as speech and gestures are responses that might be voluntarily mutable by humans, masking emotions, unlike physiologic responses (such as arterial pressure, gastrointestinal motility, secretion, perspiration, body temperature, among others visceral functions), which are detectable and inevitable patterns, i.e., less susceptible to conscious control [20,21].

The faces are differentiated in relation to size, color and geometry and are the most relevant portion of the body for emotional analysis [22,23]. Facial detection methods are increasingly relevant in studies about emotion recognition by affective computing or robots [24]. A challenge is to develop and use unobtrusive (contact free) sensors able to avoid the discomfort usually caused by the placement of physiological obtrusive sensors on people's bodies, such as EEG (electroencephalogram), ECG (electrocardiogram), EMG (Electromyogram), electrodes for galvanic skin response (GSR) and others, most commonly used [24,25].

The facial muscle innervation by branches and sub-branches of vessels supports the skin heating that can be recorded through Infrared Thermal Imaging (IRTI), which is a contact-free and highly accurate technique that enables dynamic recording of body thermal variations and has been efficient to evaluate emotions from the face [18,24,26–31]. Using IRTI, in [19], brow, eyes, cheeks and mouth were analyzed over the course of positive and negative emotions; in [32], forehead, cheek and nose were analyzed in babies during pleasant emotions; and in [33], patterns of anxiety were verified in the periorbital, nasal, chin, cheek and neck areas.

Facial detection is a crucial step for localizing and extracting face regions using the unobtrusive technique - IRTI [22]. For example, the work described in [29] reports the detection and recognition of facial expressions by the association between visual and thermal images rather than individual modalities, considering appropriate levels of light and temperature. In [34], an algorithm for automatic determination of the head centre in thermograms was proposed, sensitive to the head rotation or position. In [35], an automatic and fast method for localization of the head centre was developed using the brightness difference in thermal images, considering the facial region as the brighter region (higher temperature). In [36], computing techniques of contour and morphological detection were used for the face segmentation in thermal images. In [37], thermal models of the facial skin were used considering the background and obscured areas of the skin in the images to locate the face. In [38], a projection method on the x and y axes was applied in a grayscale image to specify the head area and centre.

Methods for facial detection that take into account the analysis of color may not be used directly for detection of the face in thermal images, because each pixel of a thermal image corresponds to the value of temperature and not the color of the face [34]. Thus, a facial detection method for color images applied in thermal cameras could be trialed, through the innovative association between low cost RGB (red, green and blue) and thermal cameras attached to a socially assistive robot for children. This type of approach has not been extensively explored in other studies.

In light of the aforementioned, the goal of this work is to propose a system based on Viola-Jones algorithm able to detect facial ROIs for emotion analysis and recognition in typically developing children. In this work, a low-cost camera system allows obtaining pairs of synchronized images, detecting ROIs using Viola-Jones in the RGB image, and then, transferring them to the thermal camera frame through a homography matrix. Thus, a comparison between a method that uses Viola-Jones to position predetermined facial regions of interest on thermal imagens and a method in which the ROIs obtained using Viola-Jones are repositioned, based on a previous manual positioning, is performed. With the ROI positioning through the synchronized images, feature extraction, classification and analysis of emotions were performed by brightness variation in the facial ROIs, correspondent to the temperature variation, from children's face during the interaction with a social robot (as an affective stimulus).

The relevance of this work is pointed out in the use of an automatic method capable of detecting regions of interest of the face with neurophysiological importance for analysis of emotions through thermal images, recorded in an unobtrusive way. There are many methods of face detection in thermal imaging, as presented above, unlike the direct detection of regions of interest, which is the main proposal of this work. In addition, the images approached here are acquired in an atypical context in which a social robot is used as an emotional stimulus in a single interaction with typically developing children.

The structure of this work comprises Materials and Methods, approaching the image acquisition system, the comparison between Viola-Jones method with and without repositioning of facial regions of interest (ROIs), experimental protocol, extraction of characteristics, reduction of characteristic vector dimensionality, classification and analysis of emotions; Results, with a description of the experimental findings about the automatic ROI methods and children's emotion analysis during the interaction with a social robot; Discussion, about the findings of the work compared to previous studies; and Conclusion, summarizing the main findings and presenting limitations and future works.

Materials and Methods

A scheme of the proposed system for emotion analysis and recognition can be verified in Figure 1.

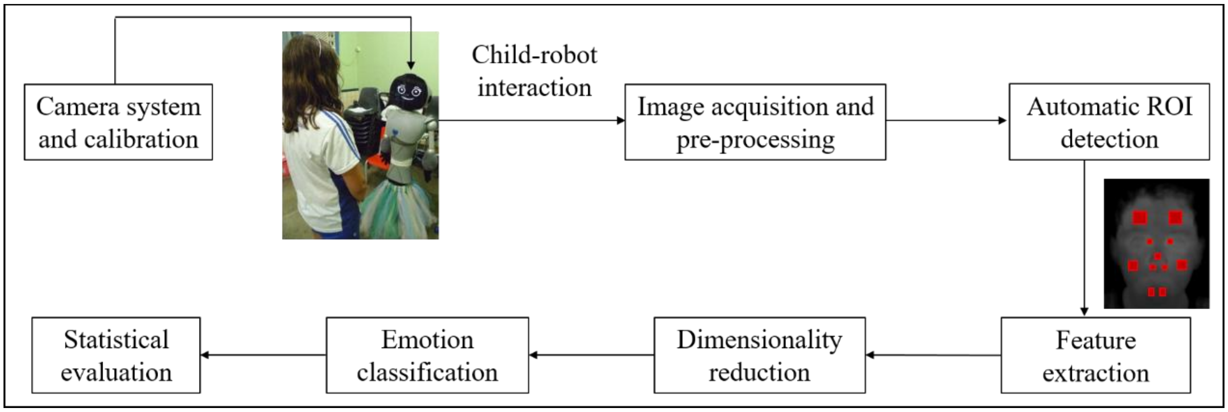

Figure 1. Overview of the proposed system for emotion analysis and recognition.

Camera system and calibration

For the infrared thermal imaging, a low cost camera, Therm-App®, was used, with spatial resolution of 384 × 288 ppi, frame rate of 8.7 Hz and temperature sensitivity < 0.07 ºC. The normalization of the thermal images acquired in gray scale consisted of a brightness rate ranging from 0 to 255, in which darker pixels correspond to lower temperatures, and lighter pixels correspond to higher temperatures. The RGB camera used in the experiment was a C270 HD Webcam (Logitech), with a resolution of 1.2 MP.

The RGB and thermal cameras were attached to the social robot head, fixed one in relation to the other so that both had approximately the same visual field. The calibration described in [39] was done once, with the synchronous acquisition of pairs of images (RGB and thermal) using a chessboard made with aluminum and electrical tape positioned in several possible angles. The images obtained were used in the OpenCV calibration software [40] that returns a homography matrix [41], which allows transformation of points from the RGB image to the thermal image. The Direct Linear Transform (DLT) algorithm used corresponding points in both images to estimate the homography matrix, as done by Agarwal et al. [43], allowing transformation between the planes of RGB and thermal images in a robust way.

Experimental procedure

The camera system attached to the robot records facial images of children during their interaction with it. The experimental procedure is following described.

This study has approval of the Ethics Committee of Federal University of Espirito Santo, under number 1,121,638. The participants of this study consist of 20 children: 10 boys and 10 girls (aged between 8 and 12 years old; mean (M) = 10.81 and standard deviation (SD) = ± 1.29) recruited from elementary schools. All they had their parents' permission, through the signatures of the Terms of Free and Informed Consent. In addition, children signed a Term of Assent, informing their wish in participating of this study. The experiments were conducted within their own school environment.

The robot of this study is called N-MARIA (New - Mobile Autonomous Robot for Interaction with Autistics), shown in Figure 2, which is a socially assistive robot developed for interacting with children with Autism Spectrum Disorder (ASD). In this work, the interaction of this robot is with typically developing children.

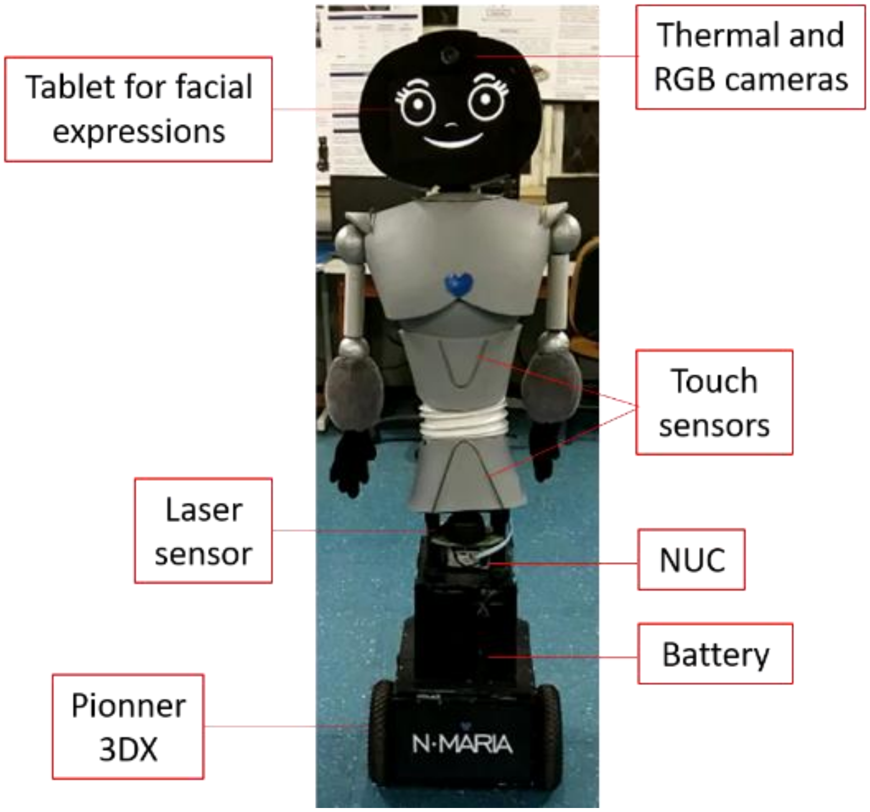

Figure 2. N-MARIA (New-Mobile Robot for Interaction with Autistics).

N-MARIA is 1.41 m tall (near to a typical child's height aged 9 to 10 years old) with a body built with soft and malleable materials (with some touch sensors on its body), enabling the protection of both internal devices and children. A mobile platform (Pioneer 3 DX) is responsible for the N-MARIA locomotion, and a laser sensor (360º LiDAR - Light Detection and Ranging) is used to locate the child in the environment. Two NUCs (Next Unit Computing) are used for control and signal processing, one being for the control of the Pioneer and LiDAR, and the other for the acquisition and processing of images and sensor signals. A tablet comprises the robot face and displays dynamically seven facial expressions. Preprogrammed dialogues are emitted through a speaker connected to the tablet (via Bluetooth). Another tablet is used by therapist to select the facial expressions, dialogues and type of robot movement, through an interface designed using C# and Unity languages. A computational server (with communication via Wireless Local Area Network - WLAN) was created to establish the communication between a NUC and the control tablet, allowing commands to be performed instantly. In spite of having the mobile feature, in this study the robot was stationary throughout the test, in order to avoid any reaction of anxiety in the child during the facial image recording.

In the test room, the temperature was kept between 20 ºC and 24 ºC, as done by [34], the luminous intensity was constant. The child was invited to sit comfortably and listen to explanations about the general activities, and be conditioned to a relaxed state for a minimum of 10 min, in order to adapt her/his body to the temperature of the room, allowing her/his skin temperature to stabilize for baseline recordings, according to similar studies carried out by [21,30]. After the relaxation period, the child was positioned in front of the robot, about 70 cm away from it.

Initially, the robot was covered with a black sheet, except for the thermal and RGB cameras. Once the child was in front of the robot, recordings of the child's face by the RGB and thermal camera were initiated before the child saw the robot (moment called "baseline") and while the experiment was carried out (moment called "test"). The child was asked to look forward without sudden movements or touching the face to ensure efficient recordings of the face.

In sequence, the black sheet that covered the root was removed, and the first dialogue (self-presentation) of the robot was started. In addition to self-presentation, prompt dialogues displayed during the experiment were related to questions, positive reinforcement and invitations. In the interaction, that lasted two minutes, the child was encouraged to make communication and tactile interaction with the robot.

At the end of the experiment, the child was invited to sit and answer a structured interview about her/his feelings before and after seeing the robot, and also about the robot structure (if the child liked it (or not), what she/he liked most or least, and what the child would change about it).

Figure 3 illustrates the child-robot interaction during the experiment in the schools.

Figure 3. Experiment setup presenting the interaction of both child and robot.

Image acquisition and pre-processing

The thermal camera has an acquisition capacity of 8 frames per second, and the RGB capacity is 30 frames per second. To obtain temporal consistency between both RGB and thermal images were simultaneously recorded using an acquisition rate of 2 images per second.

In the thermal image pre-processing, considering a fixed noise problem presented in this image, it was necessary to acquire a reference image with an object covering the entire field of view of the camera to generate an image with all pixels of same brightness. Since there is fixed noise, this reference image does not have equal pixels. Thus, whenever a thermal image is acquired, it is prepared by subtracting the reference image in order to eliminate the fixed noise. The acquisition of a reference image was made for each experiment because this noise depends on the internal temperature of the camera. Finally, a median filter was used to eliminate salt and pepper noise from the thermal image.

Automatic ROI detection

Viola-Jones algorithm

The face detection by the RGB camera uses the known algorithm of Viola-Jones [42], whereas the thermal camera records temperature variations. The homography matrix previously obtained in Section “Camera system and calibration” allows transformation between planes of RGB and thermal images in a robust way. In fact, there is no homography matrix that matches exactly points in all regions of the face (because they are not in the same plane), but the matrix obtained by DLT (explained in Section "Camera system and calibration") is used as an efficient approximation.

Using the Viola-Jones algorithm, local binary patterns in an image made it possible to detect the nose [44] and eyes [45] in the RGB image. In sequence, based on this previous information and according to proportions defined in [26,46], it was possible to detect all the ROIs accurately and automatically. Once the child's face was detected, and using the aforementioned transformation and homography matrix, the corresponding facial ROIs were obtained for the thermal image.

Facial ROIs, such as the nose, both sides of forehead, cheeks, chin, periorbital area (close to the eyes) and perinasal area (bottom of the nose) were chosen and evaluated here, as shown in Figure 4. The choice of these ROIs was based on many studies about evaluation of emotions by infrared thermal imaging, such as [30], [47] (where forehead, periorbital, nasal tip, maxillary area, cheeks and chin were tested), and [48] (where forehead, periorbital, nose tip, perinasal, chin, and corrugator were tested).

Each ROI was based on fixed size/position rectangles at key parts of the face with neurophysiological importance [30], with fixed proportions based on the width of the face [26], which are 6.49% for nose; 14.28% for forehead; 3.24% for periorbital region; 9.74% for cheek; 3.24% for perinasal region; 5.19% for chin [46].

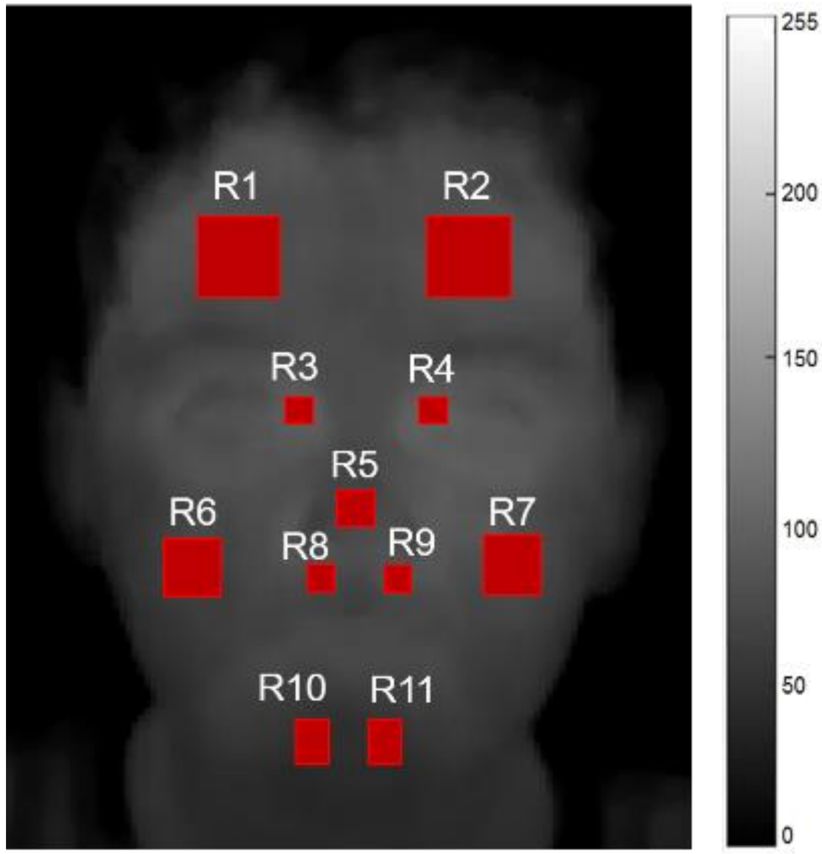

Figure 4. Facial regions of interest. R1: right forehead side; R2: left forehead side; R3: right periorbital side; R4: left periorbital side; R5: tip of nose; R6: right cheek; R7: left cheek; R8: right perinasal side; R9: left perinasal side; R10: right chin side; R11: left chin side.

Although Viola-Jones is a classic and strongly recognized method for face detection in color (RGB) image cameras, there are few studies that use it for thermal images [22]. In fact, infrared images are less clear than visible images [49]. The low-cost thermal camera used in this work is devoid of face detection, thus, the combination between both Viola-Jones method and transforming images by the homography matrix makes it possible to detect the facial ROIs in thermal images.

ROI relocation using probability based on distance error

A method was proposed to improve the accuracy during the ROI location, taking into account defined ROIs locations, which were annotated on a first frame by a trained expert (manual ROI positioning). This strategy was used to select subject-specific ROIs.

In the experiments, a fixed distance between the cameras (RGB and thermal) and the volunteer was maintained (about 70 cm), so that once the distances among the regions of interest were previously established, they did not change meaningfully during the experiment. Based on this, fixed point ($P0$) of the upper left corner of a rectangle surrounding the face was established. It is the most reliable point of automatic detection and has the coordinates equal to the height and width of the face provided by the Viola-Jones algorithm [46].

A linear error was considered, since the method proposes a correction in the distance of the regions [46]. Therefore, before applying the proposed method, a thermal image of the child was obtained and regions of interest in the image were manually placed by a trained expert. Based on $P0$, two probabilities were calculated: one relative to the distance of all the ROIs estimated by the method explained in section “Viola-Jones algorithm” in relation to the X axis and the other in relation to the Y axis. These probabilities can be described by Equations 1 and 2 and indicate the reliability of the correct position for each ROI, based on the proportion of the distances in relation to the manually defined regions. Once the two probabilities are obtained, the largest one is discarded in order to obtain the smallest possible linear error. After selecting the lowest probability of each region, the highest probability for the region of greatest confidence was chosen, and through the region of greatest probability, the other regions were repositioned using Equations 3 and 4.

$$\boldsymbol{Probx}(\boldsymbol{Pt},\boldsymbol{V}) = \frac{\boldsymbol{e}^{-|\boldsymbol{Ptx}-\boldsymbol{RVx}|}}{\sum_{\boldsymbol{i}=\boldsymbol{1}}^{\boldsymbol{11}} \boldsymbol{e}^{-|\boldsymbol{Pix}-\boldsymbol{RVx}|}}, \quad (1)$$

where $Probx(Pt,V)$ is the probability that a point Pt with coordinates (Ptx, Pty) of the image belongs to a region V in which the corresponding point of the region V is at a point with coordinates (RVx, RVy) in the reference image, and each region i (from 1 to 11) in the image with the coordinates (Pix, Piy), being considered horizontally.

$$\boldsymbol{Proby}(\boldsymbol{Pt},\boldsymbol{V}) = \frac{\boldsymbol{e}^{-|\boldsymbol{Pty}-\boldsymbol{RVy}|}}{\sum_{\boldsymbol{i}=\boldsymbol{1}}^{\boldsymbol{11}} \boldsymbol{e}^{-|\boldsymbol{Piy}-\boldsymbol{RVy}|}}, \quad (2)$$

where $Proby(Pt,V)$ is the probability that a point Pt with coordinates (Ptx, Pty) of the image belongs to a region V in which the corresponding point of the region V is at point with coordinates (RVx, RVy) in the reference image, and each region i (from 1 to 11) in the image with the coordinates (Pix, Piy), being considered vertically.

$$\boldsymbol{Pix'} = \boldsymbol{P0x} + \boldsymbol{Pmx} + \boldsymbol{Rix} - \boldsymbol{Rmx}, \quad (3)$$

where Pix' is the position in which the region i must be placed horizontally in order to correct its position considering that m is the region with the biggest probability and $P0$ has coordinates $(P0x, P0y)$, in relation to the distance between regions i and m horizontally in the reference image (that is $Rix - Rmx$).

$$\boldsymbol{Piy'} = \boldsymbol{P0y} + \boldsymbol{Pmy} + \boldsymbol{Riy} - \boldsymbol{Rmy}, \quad (4)$$

where Piy' is the position in which the region i must be placed vertically in order to correct its position considering that m is the region with the biggest probability, $P0$ has coordinates $(P0x, P0y)$, and the distance between regions i and m vertically in the reference image (that is $Riy - Rmy$).

Feature extraction

Two hundred twenty frames close to the moment in which the sheet is removed from the robot (in both baseline and test moments) were selected from each video. ROI identification was possible for images of 17 typically developing children; 7 feature values were calculated for each ROI [50] and showed in Table 1.

Table 1. Features computed in each frame. *

Feature	Formula
Mean value of the whole ROI	$f_1 = \bar{P} = \frac{1}{m \cdot n}\sum_{r=1}^{m}\sum_{c=1}^{n} P_{r,c}$
Variance from the whole ROI, organized in a vector	$f_2 = \sigma^2 = \frac{1}{(m \cdot n) - 1}\sum_{c=1}^{n}(P_{r,c} - \bar{P})^2$
Median of the whole ROI, organized as a vector	$f_3 = median(P)$
Mean of variance values in rows	$f_4 = \frac{1}{m}\sum_{r=1}^{m}\frac{1}{n-1}\sum_{c=1}^{n}(P_{r,c} - \bar{P}_r)^2$

Mean of median values in rows	$f_5 = \frac{1}{m}\sum_{r=1}^{m} median(P)$
Mean of variance values in columns	$f_6 = \frac{1}{n}\sum_{c=1}^{n}\frac{1}{m-1}\sum_{r=1}^{m}(P_{r,c} - \overline{P_c})^2$
Mean of median values in columns	$f_7 = \frac{1}{n}\sum_{c=1}^{n} median(P_c)$

* The variable P represents the ROI, m and n are, respectively, the number of rows and columns, r and c the indexes for rows and columns and f is the feature. $\bar{P}$ is the average value of all pixels of the ROI, $\overline{P_r}$ is the average of the values of row r and $\overline{P_c}$ is the mean value of the column c. Finally, $P_{r,c}$ is the pixel in the row r and column c.

Considering 11 ROIs for each frame and 7 features generated for each one, a total of 77 features per frame was obtained. In order to acquire more ROI features, the difference between the frames also computed [50]. Hence, the number of features doubled to 154 features.

Dimensionality reduction

Let $T = \{(x_1, y_1), (x_2, y_2), \ldots, (x_i, y_i), \ldots, (x_n, y_n)\}$ be the training set, where n is the number of samples, and x_i is a *d*-dimensional feature vector with class label $yi \in \{1, 2, \ldots, C\}$. The Principal Component Analysis (PCA) method based on the single value decomposition [49,51] is applied on x_i to obtain the principal component coefficients, which are used in both training and validation sets to reduce their space at 60 orthogonal components. It is worth mentioning that before applying PCA, the feature vectors of the training set were normalized, using both mean and standard deviation values as reference. Then, the validation was normalized using the same reference values (mean and standard deviation) obtained from the training set.

Emotion classification

In order to know the probability of the occurrence of an emotion in the children, characteristics were extracted (as described in section “Feature extraction”), and training was done from a previous work developed in [50]. Briefly, that work deals a study of emotion recognition in 28 typically developing children (age: 7-11 years) through the analysis of the variation of facial brightness (corresponding to the temperature variation) recorded by the infrared thermal imaging (IRTI). The children were exposed to video clips to elicit five emotions: happiness, disgust, fear, sadness and surprise. Then, a dataset with patterns was obtained to classify the five emotion classes by child, and each pattern had a total of 154 features. Those patterns corresponded to the following emotions: disgust, fear, happiness, sadness and surprise. That dataset present in [50] was used for training our emotion recognition system for the three emotions (happiness, sadness and fear). For that dataset, the subjects that presented accuracy higher than 85% were only selected for training, for which vector feature dimensionality was reduced applying PCA. Afterwards, the classifier Linear Discriminant Analysis (LDA) [52] was trained using the three emotions. Finally, after computing the principal components for the validation set, the LDA model was used to recognize the unknown patterns.

Statistical evaluation

Analysis ROI relocation by Viola-Jones

The approach using Viola-Jones based on a probabilistic analysis for automatic ROI relocation (based on the manual location as reference) was compared here with the well-known Viola-Jones algorithm. This way, from images recorded during both moments of the experiment, baseline and test, a set of 220 thermography frames randomly selected from all children, were annotated by a trained expert, selecting the following ROIs: all the face, left periorbital region, right periorbital region, tip of nose, right cheek region, left cheek, right perinasal region, left perinasal region, chin-right side, chin-left side, forehead-right side, and forehead-left side. These annotated images were used as reference to evaluate, through Euclidean distances (see Equation 5), the accuracy and precision of both Viola-Jones without ROI relocation and Viola-Jones applying ROI relocation. Euclidean distances close to zero means high accuracy.

This is an example of an equation:

$$D = \sqrt{(A_x - M_x)^2 + \left(A_y - M_y\right)^2}, \tag{5}$$

where D is the Euclidean distance, (A_X, A_y) is the coordinate obtained by the automatic method, and (M_X, M_Y) is the coordinate obtained by the manual method, with reference to the ROI relocation.

Statistical analysis employed for the comparison between both approaches for each ROI was Wilcoxon Signed Rank Test for zero median.

Brightness variation analysis

During the processing of the thermal data, from thermal imagens of only 11 children, it was possible to obtain 220 frames with all 11 ROIs identified. Thus, 220 baseline frames were obtained before the robot was uncovered, and 220 test frames were obtained after the robot was uncovered, for brightness variation analysis. Means were calculated for each one of the 11 ROIs, and t-test ($\alpha = 0.05$) was used to verify the significance of the brightness variation between baseline and test.

Results

Automatic ROI detection

The automatic way was performed by the facial tracking via Viola-Jones on the thermal image, through the homography matrix. Figure 5 presents a comparison between both Viola-Jones without ROI relocation and Viola-Jones applying ROI relocation (based on manual location as reference), obtained from baseline and test videos, computing the mean and standard error per ROIs for 20 children. It indicates smaller distance error values for the method in which Viola-Jones applies ROI relocation, for both baseline (a) and test (b).

The ROIs considered were: face, right periorbital region (RPO), left periorbital region (LPO), tip of nose (TN), right cheek (RC), left cheek (LC), right perinasal region (RPN), left perinasal region (LPN), chin-right side (RCh), chin-left side (LCh), forehead-right side (RF), and forehead-left side (LF).

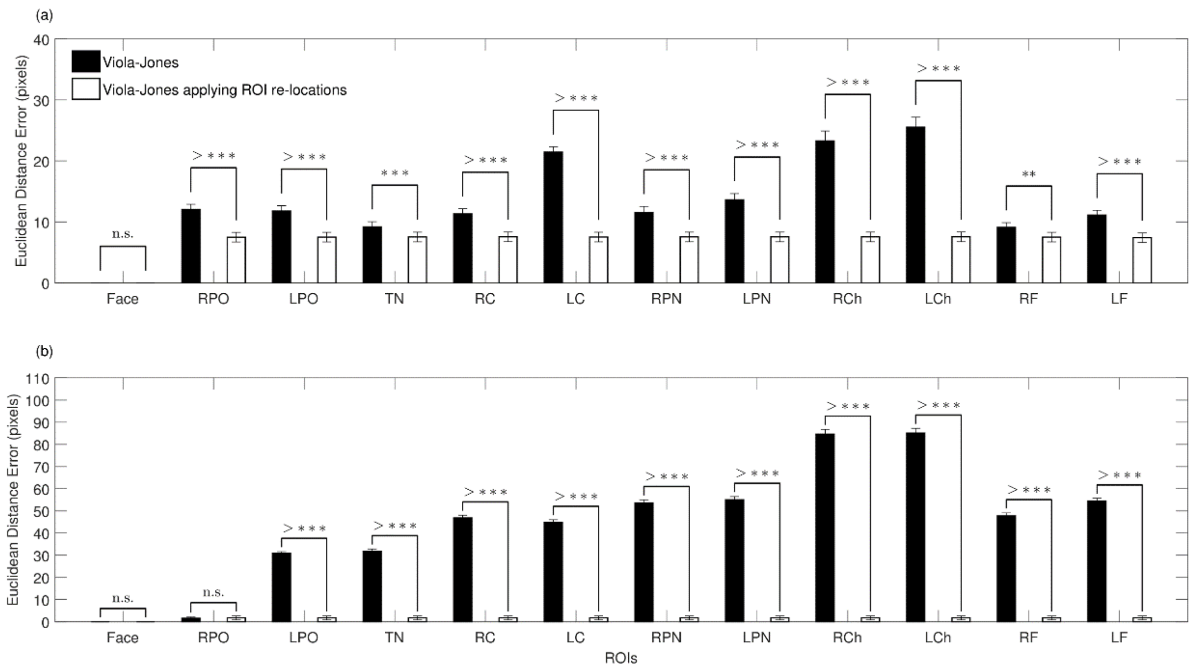

Figure 5. Comparison between Viola-Jones (without applying ROI relocations) and Viola-Jones applying ROI relocations, computing the mean and standard error per ROIs for 20 subjects: a) analysis from baseline video; b) analysis from test video. Legend: ns means no significant distance error (*p-value* > 0.05), while * (*p-value* < 0.05), ** (*p-value* < 0.01), *** (*p-value* < 0.001) and >*** (*p-value* < 0.0001) indicate significant distance error.

Emotion classification

Figure 6 shows that the happiness and surprise classes prevailed as an output from the classification analysis, for both baseline (before the child sees the robot) (Figure 6a and b) and test (after the children see the robot) (Figure 6c and d), during a single interaction of 17 children with the social robot.

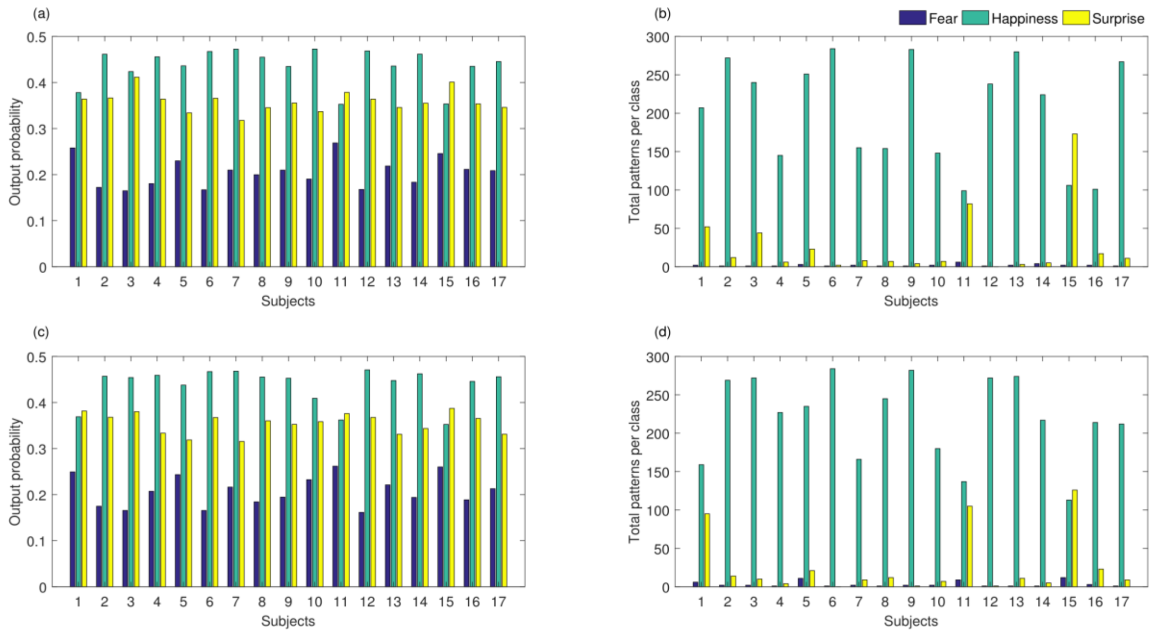

Figure 6. Profile of emotion classification from 17 children's data: a) and b) are related to the data from baseline moment, while c) and d) are data from test moment. Moreover, a) and c) present the probability obtained recognizing each known pattern.

Brightness variation analysis

Table 2 shows the brightness variation occurring in 11 children's facial ROIs when they saw the robot for the first time (test) in relation to baseline (before they see the robot). The values reveal significant temperature increases in the nose and chin mainly.

Table 2. Values of the brightness variation (BV) and *p-values* obtained from the facial ROIs when the child sees the robot. §

ROIs	**Right**	**Left**
	BV (*p*-value)	**BV (*p*-value)**
Forehead	2.07 (0.13)	1.41 (0.30)
Periorbital	1.19 (0.27)	2.49 (0.02) ↑
Cheeks	-0.56 (0.65)	3.01 (0.01) ↑
Perinasal	2.64 (0.03) ↑	1.13 (0.28)
Chin	3.84 (0.00) ↑	3.82 (0.00) ↑
Nose	3.54 (0.003) ↑	

[§] *p*-value < 0.05: significant brightness variation

"↑" indicates brightness increase or temperature increase

Children and robot interaction

Figure 7 shows the results of the interview with 11 children. Most reported a neutral emotional state before seeing the robot. On the other hand, happiness and surprise were predominant and equally reported by children after seeing the robot.

Figure 8 reveals the children's opinion about the robot's structure. The majority considered the robot beautiful. They liked its functions and did not like its size, mainly.

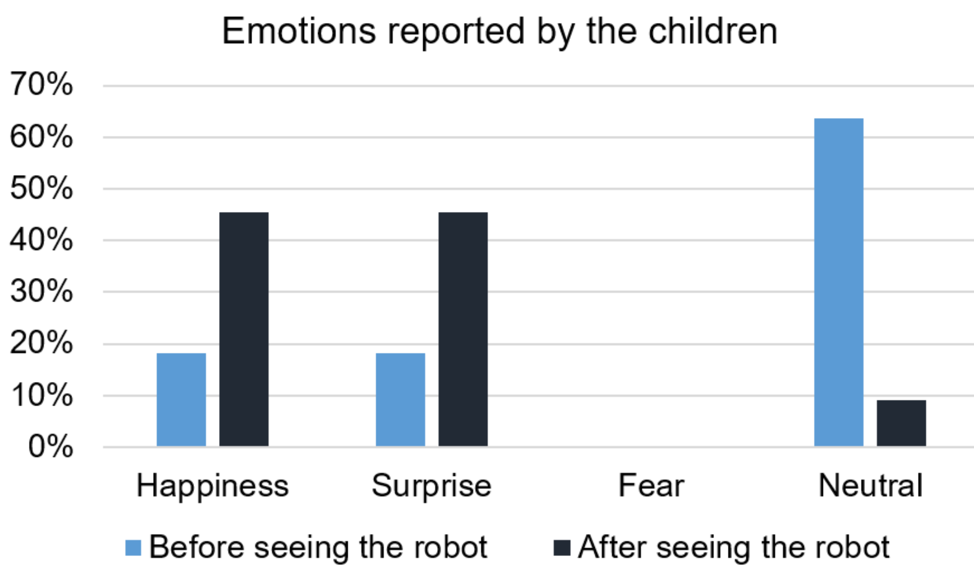

Figure 7. Emotions reported by 11 children before and after they see the robot for the first time.

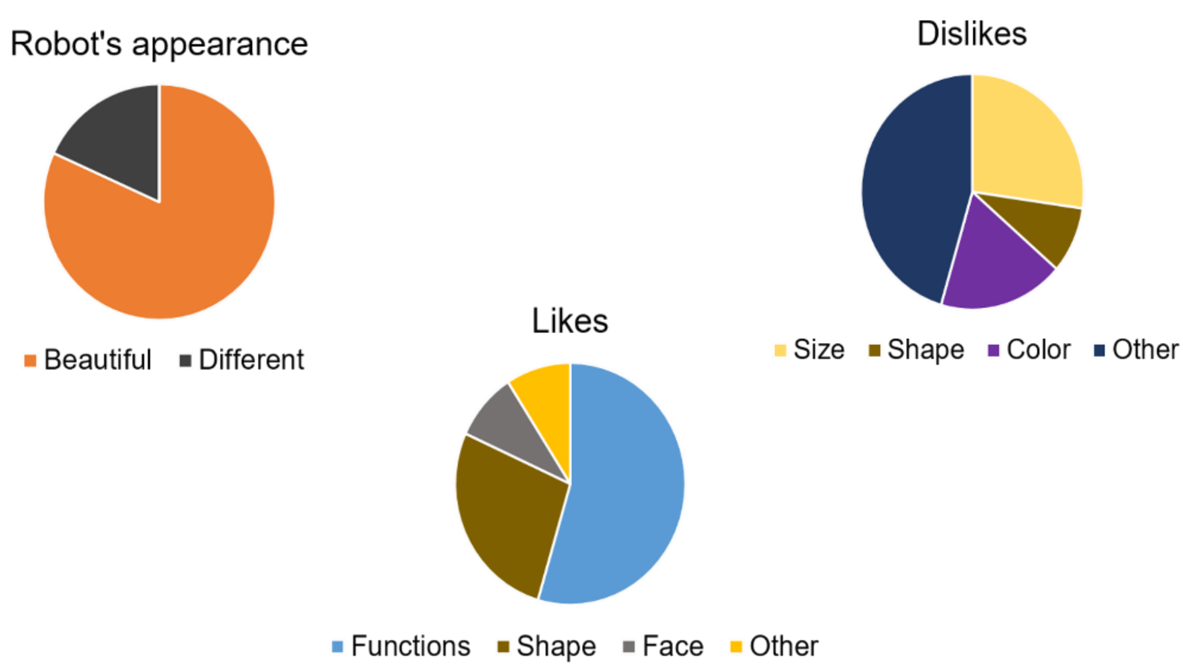

Figure 8. Children’s opinions about the robot N-MARIA during a single interaction.

Discussion

In general, automating methods aim at optimizing processes to a shorter time interval. In the case of face detection in thermal images, many works propose automatic forms of facial detection using the orientation of the head [34–38]. However, there are also some works about emotion recognition that manually segment the facial ROIs into thermal and visible images. In [49], the preprocessing work of visible images included manual eye location, angle rectification and image zoom to normalize the apex images to width versus height rectangles. In order to retain the original temperature data for the thermal analysis, the thermal images were manually segmented into five rectangular regions of interest (forehead, eyes, nose, mouth and cheeks) so that the size and radius of the facial segmentations of such infrared images from each participant were consistent. In [24], five ROIs were manually segmented in rectangles that covered mouth, nose, supraorbital (forehead) and periorbital regions, by specifying the coordinate of the bounding box around each ROI. The authors mentioned that they previously tried an automatic detection algorithm, Viola-Jones, which failed, once it detected multiples ROIs on the same region, even changing the merge threshold values in an attempt to improve the detection.

In this work, a camera system that recorded synchronized RGB and thermal images was used to detect facial regions of interest on thermal images for analysis of brightness variation (correspondent to temperature variation), in order to evaluate emotions. Thus, Viola-Jones used RGB images to detected facial ROIs that were transferred to the thermal camera plane through a homography matrix. One advantage of the Viola-Jones is that it detects and tracks the face when there is head movement, so the head remains framed with visible facial regions of interest.

Then, automatic ROI detection methods, based on Viola-Jones algorithm, considered the ROI positioning and the ROI repositioning, using the probability calculated for the place where ROIs should be, conformed to a specific manual initial marking. This comparison was carried out in two moments of the experiment, baseline and test.

The results revealed that the distance errors of ROI relocation method were smaller than for the method without ROI relocation, for both moments of the experiment (Figure 5). The errors were even smaller from the moment in which the children saw the robot (test), in which they were attentive to it and kept their heads straight and facing the cameras, and therefore, diverting their heads less. Therefore, a methodology that used a low-cost camera system that recorded images that were subjected to classic automatic face detection methods proved to be efficient for detection of regions of interest relevant to analysis of emotions in children.

These results are promising because they report the effectiveness of a method for the detection and positioning of facial ROIs in thermal images that can be performed quickly compared to the manual positioning.

The manual approach, although quite laborious, allows the ROIs to be placed very specifically and analyzed frame-by-frame by a specialist. However, considering the high number of frames, it is not possible to place the ROIs manually for large videos. On the other hand, automating ROI placement can give more ability to process a large amount of video. However, the placement may not be so accurate. If the success rate compared with the manual mode is still high, it can be acceptable and can be used to evaluate more samples. Thus, the automated system might be quite useful, if this error is small enough to be acceptable.

The brightness variation showed significant thermal increases in the nose and chin mainly (Table 2). The nose is considered a reliable indicator of stress and negative emotions [18,47]. In many studies, a temperature decrease is reported in the nose, because of the subcutaneous vasoconstriction or perspiration controlled by the sympathetic system [18,30,53]. A thermal decrease was presented in the nose of children (aged between 39 and 42 months), during situations of guilt [28], and subjects during a fear conditioning situation in a context of a mild posttraumatic stress disorder [29]. Regarding the chin, it can also be related to stress response for example, thermal imprints depicted stress-induced change over time [48]. Another study showed a relative increase in temperature of the chin in a crying episode [47].

In this work, a thermal increase occurred in the nose and chin. These increases may be related to the increment in the heart rate, generating a temperature increase in the face, which triggers a vasodilation in these regions [47], or a greater blood supply in the face coming from the facial muscle movements performed in the facial expressions when the children saw the robot [49].

In relation to the interaction of the children with the N-MARIA robot, the possible emotions that they felt were happiness, fear or surprise. The emotion classification results showed a greater probability for happiness and surprise for baseline and test moments (Figure 6). This finding reveals that the social robot was a positive emotional stimulus for the children. In addition, the results showed that Figure 7 corroborates with the results of Figure 6, revealing that the children reported happiness and surprise when they saw the robot for the first time.

All children reported that they liked to interact with N-MARIA, and the majority said the robot was beautiful. In relation to their likes, they mentioned robot's functions, shape and face; whereas as their dislikes, they mentioned robot's size and color (Figure 8). Moreover, they suggested changes relative to color, clothes, voice and body ornaments. These positive results demonstrate that the social robot was useful to stimulate positive emotions in children and was able to establish a promising interaction with them.

Conclusions

For this work, a low-cost camera system was used to record simultaneously and synchronously RGB and thermal images of the children's face to evaluate their emotions while interacting with a social robot. An automatic ROI detection method was proposed using Viola-Jones and homography matrix to ensure the ROI correct position in the thermal image. Distance errors of ROI relocation method were smaller than for the method without ROI relocation. These findings are promising, reporting the effectiveness of the automatic method based on Viola-Jones that demonstrated to be quick in relation to the ROI positioning performed by an expert.

The emotion classification showed a greater probability for happiness and surprise for both baseline and test moments of the experiment, whereas the brightness variation in ROIs showed significant thermal increase in nose and chin mainly, ROIs related to stress response.

All children had a hopeful interaction with N-MARIA, which demonstrated to be useful to stimulate positive emotions in children and able to trigger a profitable interaction with them.

In relation to limitations of this work, the small numbers of participants in the experiment can be cited. Moreover, it is necessary to improve the automating method for detecting ROIs presented in this work, in order to improve the reliability when moving the head.

Considering that robots are used in several therapies for children with autism [10,54], the results achieved in this work are promising, and future experiments using N-MARIA can study children’s interaction and emotions in an unobtrusive way.

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Chapter 3

Emotion Analysis through Infrared Thermal Imaging in Children with ASD in a Context of Social and Pedagogical Interaction with a Social Robot

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Abstract

This study presents an emotion analysis through infrared thermal imaging (IRTI) in five children with Autism Spectrum Disorder (ASD), aged 8-12 years. Facial brightness variations correspondent to temperature variation were recorded to assess three different emotions (surprise, sadness and happiness) during an interaction with a social robot, used as the emotional stimuli. The child-robot interaction was evaluated using qualitative analysis and structural questionnaires applied to the children's parents. Social abilities impaired in children with ASD such as gaze toward people, tactile interaction and communication were assessed. Pedagogical tasks were applied to the children, related to the recognition of basic emotions and objects in response to commands. Both the social and pedagogical tasks were performed in two sessions. Results showed that surprise was the emotion with the highest recognition success rate felt by the children, and significant brightness increases were found in all ROIs of the children's face. During the child-robot interaction, all children performed social skills with the robot, indicating the social robot as a suitable therapeutic and pedagogical tool for children with ASD.

Keywords: Children with ASD. Temperature Variation. Infrared Thermal Imaging. Emotions. Social Robot. Social Skills. Pedagogical Tasks.

Introduction

Studies about emotions have increased due to mainly their relevance in the interpersonal relationships. In many aspects of the day-to-day lives, emotions contribute to communication between humans, molding frequently social relationships (Nie, Wang, Shi, & Lu, 2011). Understanding emotions allows people to identify intentions of other individuals, in addition to adopt appropriate responses (Happé, 1994). Also, the ability to recognize and label emotions predicts social competence that may progress since the early childhood, benefiting the development of the human adaptive social behavior (Bal et al., 2010).

However, individuals with ASD have lack of ability to recognize emotions in themselves or in the displays of others, in addition to the disability to differentiate emotions (Happé, 1994; Rusli, Sidek, Md Yusof, & Abd Latif, 2016). This difficulty in the estimation of the emotional condition of others may be relative to the cortical impairments in discriminating stimuli, which can be found in early event-related potential in electroencephalography (EEG) peaks, due to deficits in the early stage of signal perception (Yang, Savostyanov, Tsai, & Liou, 2011). In addition to isolated neural causes, difficulties in recognizing emotions are associated with an altered attentional, perceptual and cognitive process, once individuals with ASD process faces differently from neurotypical individuals and show reduced attention to faces and facial expressions. This fact can be due to the mentalistic and emotional information conveyed by the eyes and facial expressions, which may be hard to read for individuals with ASD (Golan et al., 2010). Many studies have explored emotion recognition in individuals with ASD, taking into account their core deficits related to the impairments in reciprocal social interactions and social behaviors (Bal et al., 2010).

Unobtrusive (contact-free) devices may be an useful alternative to enable biological and behavioral analysis in studies relative to the recognition of emotions and common behavior patterns in individuals with ASD, taking into account the high sensitivity to the touch felt by these individuals (Minshew & Hobson, 2008). In fact, there is a paucity of studies evaluating autonomic activity in children with ASD through unobtrusive sensors (Bal et al., 2010). An example of physiologic sign related to emotion that might be unobtrusively evaluated is the body temperature variation, detected through infrared thermal imaging (IRTI). With this kind of technique it is possible to capture the infrared emission of the skin, which is guided by the heating coming from the increased blood flow (Ioannou et al., 2016; Wang et al., 2010). IRTI is a highly accurate technique, with low noise level (often evidenced in other physiological measures), and that can be used to evaluate both sides of the body, enabling the assessment of asymmetries in temperature in larger areas of the skin, not limiting the analysis to small regions, as with traditional electrodes used in other physiological analysis (Nhan & Chau, 2009; Rimm-Kaufman & Kagan, 1996; Stemberger, Allison, & Schnell, 2010). Studies on emotion evaluation by IRTI in children with ASD were not found in the literature to our knowledge, probably due to the difficulty in dealing with “uncooperative subjects”, such as is the case of individuals with ASD (Rusli et al., 2016). Moreover, experiments in which children are part of the study are challenging, due to the children’s spontaneous behavior (Zhou, Tsiamyrtzis, Lindner, Timofeyev, & Pavlidis, 2013).

Assistive robotics has been increasingly used in customized therapy and education intervention plans for children with ASD (Costa, Lehmann, Dautenhahn, Robins, & Soares, 2015; Dautenhahn, 2003; Feil-Seifer & Matarić, 2008; Huijnen, Lexis, Jansens, & de Witte, 2016, 2017; Warren et al., 2015). For children with ASD, robots are considered predictable, simpler and easier to understand than humans (Duquette, Michaud, & Mercier, 2008; Ben Robins, Amirabdollahian, Ji, & Dautenhahn, 2010). Thus, an interaction between children with ASD and robot might overcome barriers often found by these children in a face-to-face interaction with people (Huijnen et al., 2017).

Some studies targeting to find behavioral and social features of these children have been carried out in order to improve their social interaction and behavioral disorders and increase their life quality and autonomy (Cabibihan, Javed, Ang, & Aljunied, 2013; Kim et al., 2013; Scassellati, Henny Admoni, & Matarić, 2012).

These social interaction impairments might be related to dysfunction of the upper temporal sulcus region involved with emotional and cognitive components of autism (Allison, Puce, & McCarthy, 2000) and engaged with movements of the eyes, hands, mouth and body, social perception, imitation and perception of the human voice (Allison et al., 2000; Belin, Zatorre, Lafallie, Ahad, & Pike, 2000; Blakemore & Decety, 2001; Rizzolatti, Fogassi, & Gallese, 2001). Moreover, dysfunctions in the temporal region may explain the poor eye contact during conversation, difficulties in accessing the brain information to infer mental and emotional states of the people, and injuries of essential skills for interpersonal communication in individuals with ASD, which trigger impairments in their social interaction and expression of feelings (Klin, Jones, Schultz, & Volkmar, 2003; Scassellati et al., 2012).

Defective social characteristics in ASD also generate difficulties in understanding own and other people's emotional and mental sates (Theory of Mind) and interpreting nonliteral language, such as sarcasm and metaphor (Huijnen et al., 2016; Ozonoff & Miller, 1995; Williams White, Keonig, & Scahill, 2007). Thus, detecting these difficulties and establishing collective interactions and relationships in these children is crucial in the developing of their emotional reciprocity and intrapersonal interaction (Bal et al., 2010; Golan et al., 2010).

Considering the interpersonal interaction impairment in ASD (Derosier, Swick, Davis, McMillen, & Matthews, 2011; Williams White et al., 2007), a number of studies show an increase of the interaction between children with ASD and parents, caretakers and others, when robots are used to mediate the interaction (Kim et al., 2013; Kozima, Michalowski, & Nakagawa, 2009; Valadão et al., 2016).

In fact, social robots have been widely used as tools for stimulation of communication and social skills in children with ASD, such as eye gaze, imitation, turn taking, tactile interaction, joint attention, shared engagement and others (Goulart et al., 2018; Kim et al., 2013; Kozima et al., 2009; Ben Robins, Amirabdollahian, et al., 2010; Suzuki & Lee, 2017). For example, the anthropomorphic robot KASPAR makes movements of head and arms, articulating gestures, to interact with these children, and uses touch sensors to analyze tactile interaction between child and robot (Huijnen et al., 2017; Ben Robins, Amirabdollahian, et al., 2010). The robot doll (ROBOTA) allows a bodily interaction through imitative games and other skills of social interaction, as eye gaze, touch and joint attention (Duquette et al., 2008). A model of dinosaur-robot, PLEO, expresses emotion and attention through body movement and simple vocalizations, stimulating verbalization and interaction with other people (Kim et al., 2013). A creature-like robot, KEEPON (a little yellow snowman) performs emotional and attention exchange and encourage children to practice interpersonal communication in a playful and relaxed mood, facilitating their social interaction not only with the robot, but also peers and caretakers (Kozima et al., 2009; Kozima, Nakagawa, & Yasuda, 2005).

The goals of this work are to evaluate emotions in children with ASD during their interaction with a social robot; evaluate this interaction (through social and pedagogical tasks) and the robot's functions by professionals of diverse areas of education and therapy field, using the System Usability Scale (SUS) (Brooke, 2013; Lewis & Sauro, 2009) in addition to a structural questionnaire, in order to verify if our social robot is a potential tool to stimulate social skills in children with ASD and aid pedagogical performances. SUS allows caretakers to measure and classify the ease of using (usability) of the social robot as an interactive tool for children with ASD, and the structural questionnaire allows parents to compare the children's behaviors before and after the interaction with the robot, during two sessions.

The motivation of this work is based on difficulty that individuals with ASD have in understanding and expressing emotions. Moreover, it is known that children with ASD have interest in robots. Then, evaluating emotions in children with ASD in an unobtrusive way, through temperature variation recorded by a thermal camera attached to the robot is interesting and innovative. In addition to evaluate emotions, we demonstrate here that the robot can stimulate social interaction skills in children with ASD, such as eye gaze, tactile interaction, communication and joint attention, and be used as a tool for pedagogical tasks. We consider that studying emotion recognition, social skills and pedagogical tasks in children with ASD are important to their process of social and cognitive development, allowing the integration of these children into society and contributing to their development of a socially acceptable behavior. The increase of researches with valuable results about the application of robots to behavioral and educational therapies in children with ASD is considerable, however, the use of robots for this purpose is still in a relatively early stage (Diehl, Schmitt, Villano, & Crowell, 2012; Huijnen et al., 2016). Therefore, our study addresses the therapeutic areas in which robots can really add value and benefit the development and autonomy of children with ASD.

Material and Methods

This work was approved by the Ethics Committee of the Federal University of Espirito Santo (UFES, Brazil), under number 1,121,638, and took into account the signature of the Terms of Free and Informed Consent by the parents or legal guardians of the selected children.

Participants

This study involved the participation of five boys aged 8 - 12 years (M = 9.8 and SD ± 1.6), diagnosed with mild to moderate levels of ASD. They were recruited from the Association of Friends of the Autistics of the Espirito Santo state (Brazil), firstly through a presentation about our research given to professionals and parents of these children. Then, a semi-structural survey was applied to their parents, such indicated by APS (American Psychiatric Association, 2013), evaluating children’s specific features related to general data, daily life, behavior and social interaction (APPENDIX A). The general data consisted of age; date of birth; date of ASD diagnostic; ASD level; height; weight; other neurological diseases; and visual/auditory impairment. The daily life data were attendance at regular school; usage of specialized health services; food restriction; usage of drugs; allergies; (in)dependence in locomotion, hygiene, clothing and eating; favorite foods and tasks; hated foods and tasks; and access to technology. The behavior data were about humor; aggression; depredation of objects; stereotyped movements; things/situations that catch attention; situations that cause disappointment or happiness; happiness expression; sadness/angry expression; fear or phobias; experienced traumas; echolalia; speaking in third person; sensory sensitivity; and unusual behaviors. The social interaction data were about acceptance of rules; accomplishment of orders; eye gaze; verbal and non-verbal communication; imitation; joint attention; and participation and understanding of games.

The main inclusion criteria to the children’s selection was the absence of traumatic experiences and phobias. The exclusion criteria were the occurrence of neurological or other diseases that affect the development of the brain, use of glasses (as those difficult facial image recordings), use of medicines (as some drugs can interfere with the adrenergic system), and moderate-to-severe levels of ASD.

Social Robot: N-MARIA

In ASD, individuals have difficulty in understanding facial expressions and other social cues, and present anxiety in unusual situations. Thus, these individuals prefer predictable and stable environments (Michaud, Duquette, & Nadeau, 2003; Wong & Zhong, 2016). These aspects were took into account to build the robot N-MARIA (New-Mobile Autonomous Robot for Interaction with Autistics), following recommendations of

(Cabibihan et al., 2013; Giullian et al., 2010; B Robins, Otero, Ferrari, & Dautenhahn, 2007; Woods, 2006).

N-MARIA is a social robot that has a dynamic face that expresses six basic emotions (happiness, sadness, anger, disgust, fear, surprise, and neutral), vocalizations with ready dialogues, autonomous locomotion, safe and entertaining structure composed of soft materials, touch sensors and embedded thermal and colorful cameras (Figure 1).

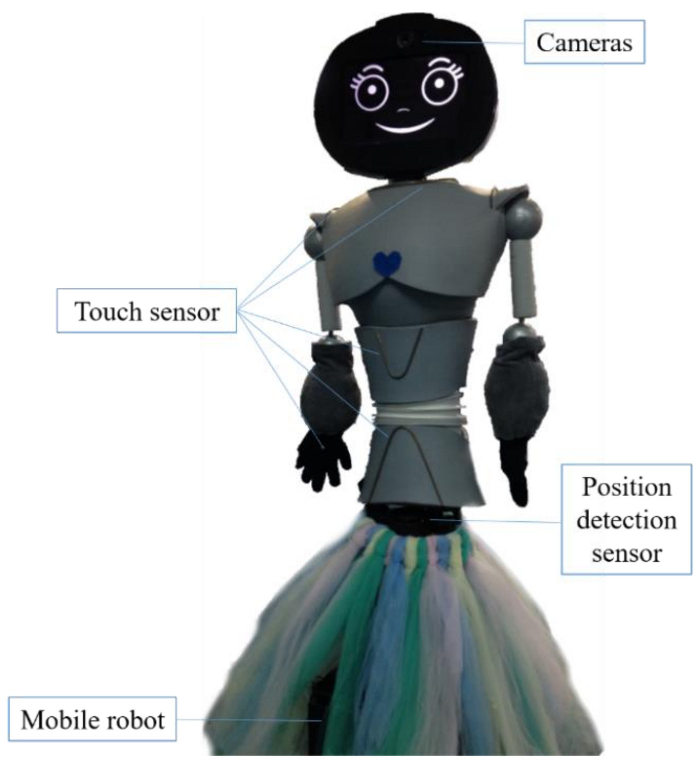

Figure 1. Robot N-MARIA developed to interact with children with ASD.

It has 1.41 m height, near to a typical child's height aged between 9 and 10 years. N-MARIA uses the mobile platform Pioneer 3 DX for its locomotion, and has a 360° laser sensor (LiDAR - Light Detection and Ranging) to detect the child's localization in the environment. Two NUCs (Next Unit Computing) process the control algorithm of the robot, being one in charge of controlling the robot and the LiDAR, and the other for data acquisition from the touch sensors and facial images, and also to control the dynamic face and dialogues of the robot. A colorful skirt is used to hide the Pioneer, battery and NUCs, and the thermal camera (used for facial image recording) is hidden at the top of the robot's head. The thermal camera is a low-cost camera (Therm-App) with spatial resolution of 384 × 288 ppi, frame rate of 8.7 Hz and temperature sensitivity < 0.07 ºC. The normalization of the thermal images was done in gray scale, characterizing a brightness rate that ranges from 0 to 255, in which darker pixels correspond to lower temperatures, and lighter pixels correspond to higher temperatures.

N-MARIA can be controlled by therapist (for social and pedagogical activities with children), using a tablet, which contains a graphic user interface (GUI) to enable the robot to perform all the preprogramed commands.

Experimental Sessions

Each child participated in two sessions of interaction with the robot, in distinct days, one in which the robot remained stopped (to avoid any reactions of anxiety or fear by the child) and another in which the robot moved around. The mean duration of the first session was 50 minutes, whereas the second session lasted 30 minutes.

In each session, the social interaction and pedagogical tasks were evaluated. Regarding the social interaction, the following social skills were chosen based on our previous works (Christiane Goulart et al., 2018; Valadão et al., 2016): eye gaze with the robot (revealing interest or lack in interacting with it), proxemics (approximation or escape), communication (answers to robot's questions and word repetition), tactile interaction and response to commands. Regarding the pedagogical tasks, two activities were proposed: emotion recognition through the robot's expressions and object recognition required by it.

The experimental room setup can be seen in Figure 2. The child is positioned in front of the robot, two researchers stand behind the robot and the mother watches the experiment close to the researchers (Figure 2b). At the right of Figure 2a, a table contains items for the object recognition activity, and there are two chairs used to the activity about recognition of the robot's emotion expressions, through a task of association and collage.

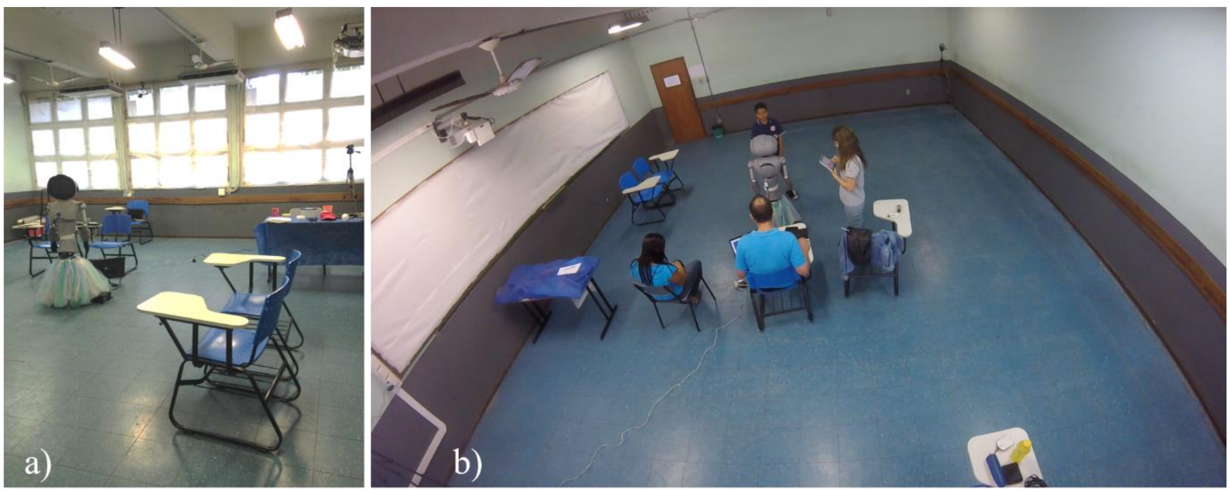

Figure 2. Experiment room: a) anterior view and b) posterior view. Four people make up the experiment room: two researchers, mother and child; two external video camera are positioned at opposite extremities of the room, and one in the ceiling. A table has several objects for the pedagogical tasks about object recognition, two chairs are used for pedagogical activity about recognition of emotions, and a temperature sensor is used for temperature monitoring in the room.

Image recordings obtained from four cameras were used to evaluate the social skills and the performance of the pedagogical tasks during the two sessions. Two video cameras were placed in room extremities, one in the room ceiling, and RGB camera in the robot's head, allowing front and rear images of the robot and the child, in addition to images of the child's face and the whole room environment.

In the test room, the temperature was kept between 20 and 24 ºC, and the luminous intensity was constant, such as done by (Marzec, Koprowski, & Wróbel, 2015). The child and his mother were invited to sit comfortably for explanations about the general activities and the body adaptation to the temperature of the room for a minimum of 10 min, such as recommended by (Ioannou, Gallese, & Merla, 2014; Nhan & Chau, 2010).

In both sessions, initially the robot was covered with a black sheet (to prevent the child's distraction, which could fail the experiment), except the camera system of the robot's head. The child was positioned 70 cm away from the robot (distance previously defined). Other distances in relation to the robot were marked on the room floor in order to assess possible proximity that the child could have in relation to the robot when seeing it, for surprise or curiosity. Thus, the assessment of this proximity was based on the concept of proxemics (Hall, 1966) to describe the spatial distances that individuals maintain in various social and interpersonal situations, varying according to age, culture, type of relationship and context (Rios-Martinez, Spalanzani, & Laugier, 2015). Then, the distances marked on the room floor corresponded to 0.45 m (intimate zone), 1.2 m (personal zone), 3.6 m (social zone), and > 3.6 m (public zone) (Hall, 1966; Rios-Martinez et al., 2015). Away 70cm of the robot, the child was initially inside the personal zone.

First session: robot stopped

The purpose of the first session was the child's familiarization with the experimental room and the robot (Costa et al., 2015). Thus, this session allowed the child to identify instantly the structure and some functions of the robot, perceiving that it was harmless. The protocol experimental was divided into two parts: social interaction and pedagogical tasks.

Social interaction

The social interaction lasted about three minutes, in which the robot was uncovered and dialogues of self-presentation, questions to the child and invitation to the tactile interaction were triggered in the robot by the researchers ("Hello! My name is N-MARIA. What's your name?"; "I like to play, spin and talk. What do you enjoy doing?"; "Come to see me. Touch my arms and my hands."). In sequence, the child was allowed touching and knowing freely the robot, interacting with it. The researchers, then, invited the child to see some parts of the robot and touch them, if wished. Thus, eye contact, communication, tactile interaction, joint attention and approximation were stimulated in the social interaction.

Pedagogical tasks

Subsequently, pedagogical tasks consisted of the recognition of emotion expressions of the robot through a collage and association exercise, in addition to the recognition of objects used in the daily life in a ludic context. This last pedagogical activity was suggested by professionals of the Association of Friends of the Autistics of Espirito Santo state, who reported about the importance of the object recognition and speech for daily activities, in order to assist the development of other activities, such as organization of materials of school and home, theater, music, storytelling, among other tasks.

Robot's emotion recognition

The child and researchers sat down to perform the activity of the robot emotion recognition. As some children with ASD have difficulty in speaking, an activity of association, collage and word repetition was proposed. Six emoticon stickers, corresponding to six emotions (happiness, sadness, fear, anger, disgust and surprise) were shown to the child in order to know if he recognized them. Thus, the names of the emotions represented in the stickers were asked for the child. Once recognized the emoticons, the sequence of the robot's six expressions was displayed as shown in Figure 3, and the child was encouraged to tell the name of the robot's emotions, recognize the corresponding emoticons and paste the stickers into a paper in the sequence displayed by the robot.

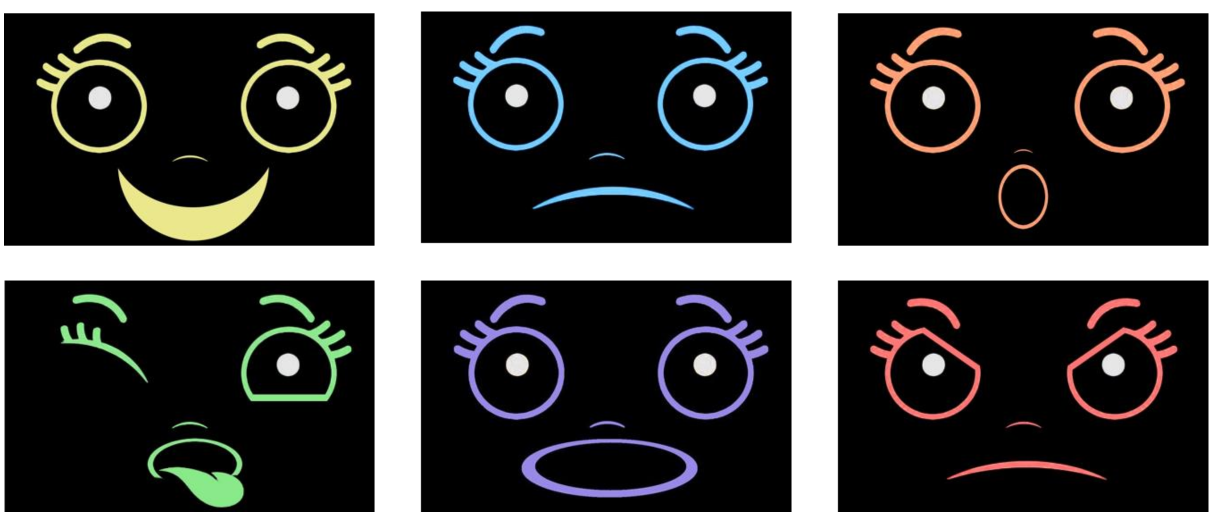

Figure 3. Emotion expressions of the robot displayed to the children in the following sequence: happiness, sadness, surprise, disgust, fear and anger.

Object recognition

The object recognition activity was proposed based on a context in which N-MARIA goes to the beach. Then, an invitation was triggered: "Let's go to the beach?", and specific objects among several other items were required to be put inside a beach bag ("Put in my bag..."). The required objects were as follow: bucket, cap, glasses, comb, towel and sandals. An example of this activity was demonstrated by the researchers. After each word told by robot, the dialogue “Let’s go to repeat?” was triggered. When the child achieved success in the accomplishment of the activity, the researchers triggered the congratulatory sentence or positive reinforcement (“Very good!”). In the opposite case, the motivation sentence (reinforcement of encouragement) was triggered, stimulating him to try again (“Let’s go to try again?”).

At the end of the experiment, a structured survey of seven questions was applied to their mothers, in order to evaluate their child's unusual behaviors during the first session. The questions were: 1) In your opinion, how did your son feel just before seeing the robot? 2) Do you think he liked or did not like seeing the robot? 3) What is your opinion about his interaction with the robot? 4) Any comment about the child-robot interaction? 5) In your opinion, how did your son feel after seeing the robot? 6) Did your child have any unusual behavior with the robot? Which? 7) In your opinion, what did the robot stimulate in your child?

Robot usability

In order to verify the usability of the robot and implement improvements for the second session, four professionals, two teachers, a psychologist and an occupational therapist were invited to control the robot, testing its functions and responding to a structured survey, which consists of an usability scale based on three questions about their opinions relative to the aid of the robot in their sessions/classes with children with ASD, the improvements for the robot to its usage as a therapeutic or pedagogical tool, and their own experiences with N-MARIA. Also, the System Usability Scale (SUS) (Brooke, 2013; Lewis & Sauro, 2009) was used, which consists of ten items for evaluating the robotic system. The ten items of SUS receive the score of five points scale numbered from 1 ("strongly disagree") to 5 ("strongly agree"), and the number 3 is the center of the rating scale (in case of no response). The items were adapted for this study, which are described below, such as suggested by (Lewis & Sauro, 2009):

1. I think that I would like to use this robot frequently.
2. I found the robot unnecessarily complex.
3. I thought the robot was easy to use.
4. I think that I would need the support of a technical person to be able to use this robot.
5. I found the various functions in this robot were well integrated.
6. I thought there was too much inconsistency in this robot.
7. I would imagine that most people would learn to use this robot very quickly.
8. I found the robot very cumbersome to use.
9. I felt very confident using the robot.
10. I needed to learn many things before I could get going with this robot.

For calculating the SUS score, a contribution is provided to the score of five points given to the ten items. This contribution ranges from 0 to 4 (four is the most positive response). For odd items (worded positively), 1 is subtracted from the value given by the user, and for even items (worded negatively), the value given by the user is subtracted from 5. Then, scores are summed together and multiplied by 2.5 to get the score, which ranges from 0 to 100. Values greater than 68 are considered above average, while values smaller than 68 are below the average (Brooke, 2013).

Second session: robot in movement

Like the first session, the protocol experimental was divided into social interaction and pedagogical tasks. During the social interaction, after the robot's questions to the child about his name and things that he likes doing, the robot displayed the six emotion expressions in its face in the sequence: happiness, sadness, surprise, disgust, fear and anger, and the researcher asked the child what N-MARIA was feeling. Afterwards, the invitation to a tactile interaction was triggered, such as aforementioned. In sequence, to indicate the robot locomotion, the researcher triggered the following robot's invitations: "Let's go to walk now? Come to walk by my side."; "Hold my hand." Then, the researcher demonstrated the following movement modes performed by the robot (Christiane Goulart et al., 2018): "walking mode", in which the robot moves in a straight line when a button of its hand is pressed; "follower mode", in which the robot moves away when a person approaches; or it approaches when the person moves away. Once the robot movement modes were demonstrated, the child was encouraged to perform them in sequence, with the researcher and alone.

After the robot's locomotion, the object recognition activity was performed in a similar way to the first session, except in three situations: at the context in which N-MARIA went to travel by issuing an invitation (the robot said "Let's go to travel?"); the required objects were to be put inside its suitcase ("Put in my suitcase…: umbrella, cap, comb, t-shirt, pants, toothbrush"); and the addition of a robot's spin when the child accomplished the activity successfully.

Finally, the same structured survey applied during the first session to the mothers was applied in the second session, with another question: "Did you notice any difference in your child's behavior as the robot moved?"

In addition to the questionnaires, note taken and images of video cameras supported the analyses about the performance of the social interaction and pedagogical tasks of the children.

Emotion analysis by IRTI

The robot has a thermal camera to record the children's facial images, which was triggered since when the child was positioned in front of the covered robot to the beginning of the tactile interaction (when the child was allowed approaching towards the robot, coming out of the camera focus). It was possible to evaluate images from the children's faces only at the second session, since the children remained in front of the robot more frequently than in the first session. The process of familiarization presented in the first session was very important for the child to feel more comfortable and safer in the second session, knowing the functions and structure of the robot and the activities that could be performed with it.

Images of three children with ASD were considered profitable to the processing, since the children remained positioned close to the robot (around 70 cm) determined as efficient distance for recording with the thermal camera. In the image processing, 11 regions of interest (ROIs) of the face (right and left sides of the forehead, periorbital, perinasal and chin regions, cheeks and nose) were manually marked in the first frame, and later, they were automatically positioned in the following frames. A manual checking was performed to discard ROIs not correctly positioned, enabling an appropriate selection of frames for the analysis (Goulart et al., 2019(a)).

Three hundred and twenty frames were obtained in the period before removing the cover of the robot (baseline) and after removing the cover (test). In this case, the robot was the emotional stimulus for these children, and three emotions were investigated: happiness, surprise and fear.

To keep the children correctly positioned and in front of the robot, the researcher asked the child to count from 1 to 30, allowing recording the baseline. They counted to 30 together the experimenter, and then, the cover was took off and the children saw the robot.

The image (pre-)processing comprising the face detection and ROIs, the extraction of 154 features, the dimensionality reduction and the emotion classification for the three emotions were accomplished according to our previous studies (Goulart, et al., 2019(a) and (b)).

A statistical evaluation allowed verifying the significance of brightness variation of the children’s faces, through means calculated for each one of the 11 ROIs and all face, in addition to the use of the t-test ($\alpha = 0.05$), which compared the brightness variation between baseline and test.

Results

The obtained results consist of analysis of the performance of the social interaction and pedagogical tasks mediated by the social robot (N-MARIA) built for interaction with children with ASD according to thermal image recordings. The social interaction skills evaluated during two sessions were: eye gaze, proxemics, communication, tactile interaction and attending to commands. The pedagogical activities included the emotion expression recognition by an association and a manual task in addition to the objects recognition, in order to stimulate the speech and response to commands.

Eye gaze and tactile interaction

During the first three minutes of the sessions (from the moment in which the sheet was taken off of the robot), eye gaze and tactile interaction were evaluated by counting how many times the child looked away from the robot and touched it (Valadão et al., 2016), such as shown in Figure 4.

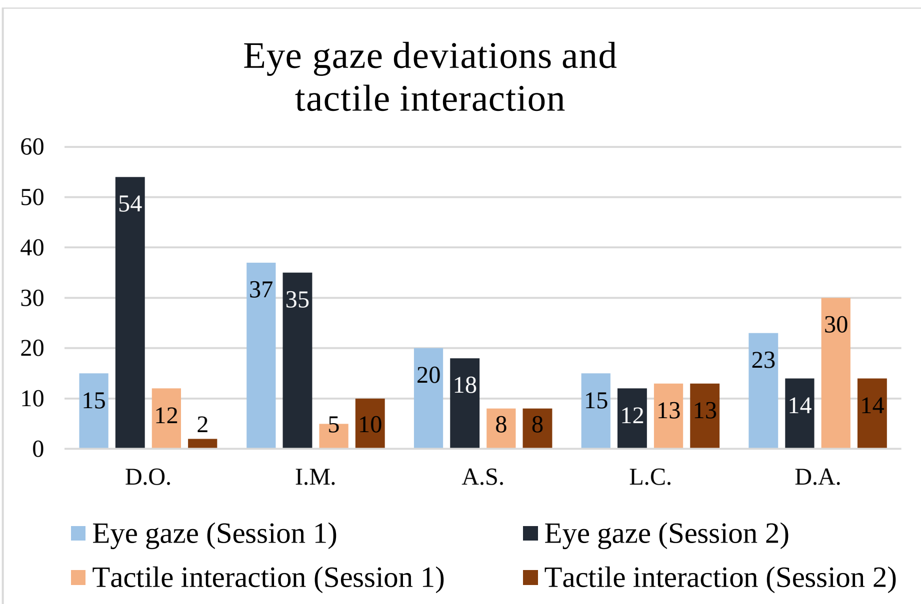

Figure 4. Results of eye gaze deviations from the robot and tactile interaction during two sessions. Regarding the eye gaze, the numbers refer to the times in which the gaze was diverted from the robot, usually higher in the first session. In contrast, tactile interaction

was defined by the number of touches and the picking actions with each one of the hands, which were encouraged in the first session and performed spontaneously in the second session.

The eye contact towards the robot was predominant during the second session (Figure 4), taking into account the smaller gaze deviation numbers. Considering the eye gaze deviations in relation to the robot, the most of them corresponded to eye gaze towards the researcher in a joint attention, such as shown in Figure 5.

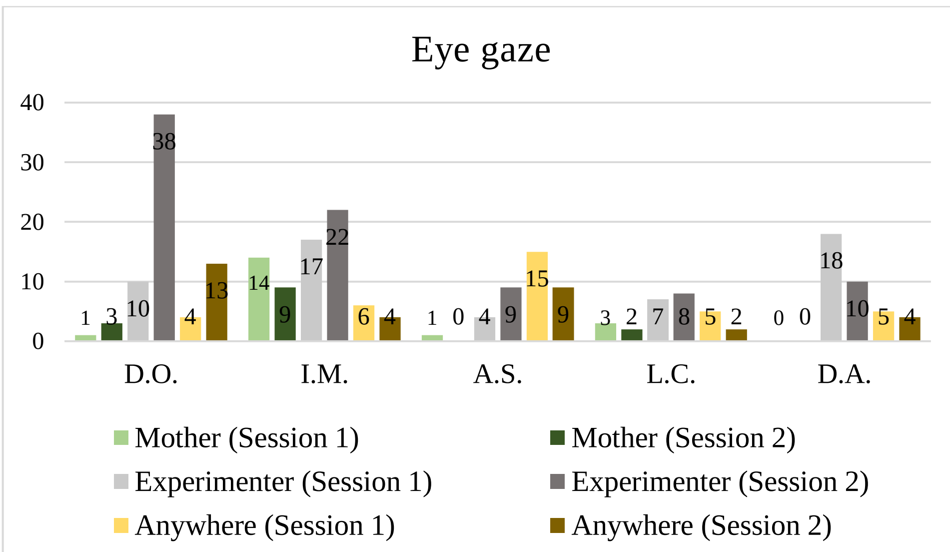

Figure 5. Eye gaze performance. The eye contact was made with the mother and the researcher mainly.

Figure 5 shows the general increase of the eye contact with the experimenter in the second session. N-MARIA can be considered a mediator in the interaction between the child and the researcher. In general, eye contact towards the experimenter was performed by all children in the following situations: when N-MARIA talked, the child usually gazed the researcher to answer the robot's questions; when N-MARIA showed its emotional expressions, the child answered the names or imitated them gazing the researcher; and during the pedagogical tasks, seeking approval about the object taken after the robot's requirement. Moreover, joint attention was performed during the first session, in the moment of encouragement of the tactile interaction, in which the researcher showed the robot's structure to the child.

Robot's parts touched by the children

The tactile interaction was performed under the researcher's encouragement during the first session, therefore a larger number of robot's regions were touched. Then, a joint attention was performed during this session, in which the experimenter pointed parts of the robot's structure to the child. On the other hand, tactile interaction was spontaneously performed during the second session. The robot's body parts more touched by the children are shown in Figure 6.

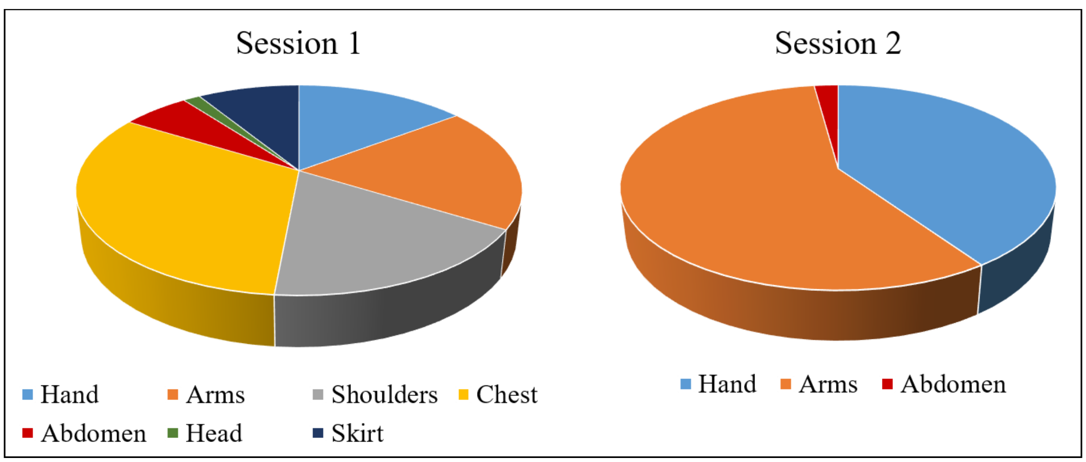

Figure 6. Areas of the robot more touched by the children with ASD. During the first session the tactile interaction was encouraged by the researcher. In the second session, the touches were performed spontaneously on arms and hands mainly.

Proxemics

General spontaneous escape or approximation towards the robot were evaluated during two sessions, considering the interaction zones, such as intimate zone (≤ 0.45 m), personal zone (between 0.45 m and 1.2 m), social zone: (> 1.2 m) and public zone: (> 3.6 m). The children were in the personal zone in the beginning of the experiment. According to Figure 7, the children stood close to robot in general, and the majority of them did not exceed the personal zone during the second session, remaining comfortable and close to the robot.

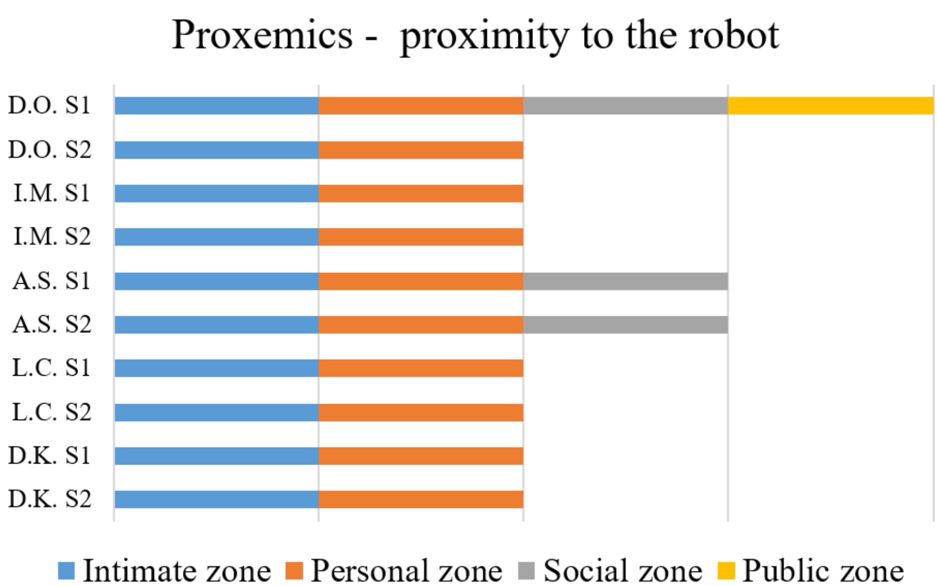

Figure 7. Children's proximity to the robot during the first and second sessions (S1 and S2). The highlighted zones are those that the children occupied during the interaction.

It was observed that the children seemed to be more comfortable in environments with the presence of the robot throughout the sessions, since they knew and anticipated the robot's actions.

Communication and response to commands

To characterize the communication, three situations were evaluated: 1) Answers to the robot’s questions (“what’s your name?” and “what do you like to do?”); 2) Naming emotions; 3) Repetition of the object name required by N-MARIA. Table 1 shows the accomplishment of the communication during two sessions, represented by the filled squares.

Table 1. Verbal communication situations performed by the children.

Children	Answers to the robot				Naming emotions				Objet name repetition			
	Session 1		Session 2		Session 1		Session 2		Session 1		Session 2	
	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
D.O.	■		■		■		■		■		■	
I.M.	■		■		■		■		■		■	
A.S.	■ ¨			■		■ *		■ *	■		■	
L.C.	■		■		■		■		■		■	
D.A.	■		■		■		■		■		■	

¨ He only answered his/her name

***** He imitated the robot’s emotion

To attend the commands, the children should perform the robot’s requirements, such as touching its arms; taking the required objects and putting them inside its bag or suitcase; and walking with it, holding its hand. Table 2 shows the response of the commands by the children during the sessions, demonstrated by the filled squares.

Table 2. Commands requested by the robot and their responses by the children.

Children	Touch the robot				Taking objects				Walking with the robot	
	Session 1		Session 2		Session 1		Session 2		Session 2	
	Yes&	No	Yes+	No	Yes*	No	Yes*	No	Yes	No
D.O.					4		5			
I.M.					5		4			
A.S.					3		§			
L.C.					5		4			
D.A.					4		5			

& Together with the researcher

+ Spontaneously

* Number of outcomes from five required objects during the first session, and six objects during the second session

§ He did not perform appropriately the task. He put all the items on the table inside the suitcase

All the children touched the robot either spontaneously or encouraged by the researcher. After the robot's commands, most of the children accomplished successfully the taking of the required objects and all they walked with the robot, holding its hands.

Figure 8 shows some moments of the sessions, in which the children are interacting with the robot and the researcher and performing pedagogical tasks. It is relevant to mention that at the end of the sessions, while the mothers answered the questionnaire, the children were totally relaxed, exploring the room scenario, touching the robot N-MARIA, hugging it and taking pictures with it.

Figure 8. Children with ASD during the sessions. Examples of tasks performed by the children, such as eye gaze, tactile interaction, joint attention and response to commands.

Mothers' survey assessment

Table 3 shows the mothers' answers to the survey applied at the end of the first session.

Table 4 shows the mothers' answers to the survey applied at the end of the second session.

Table 3. Mothers' answers during the first session.

Mothers' answers / Questions	**How do you think your child felt just before seeing the robot?**	**Do you think he/she liked seeing the robot?**	**Do you think he/she interacted well with the robot?**	**Any comment on the interaction?**	**How do you think your child felt after seeing the robot?**	**Did your child have any unusual behavior with the robot?**	**What do you think the robot stimulated in your child?**
D.O.	Surprised	Yes	Yes	No	Surprised	No	Communi-cation and interaction
I.M.	Happy	Yes	Middling	At the beginning, he was surprised, after a while, he relaxed	Happy	No	He remained calm in an unusual situation
A.S.	Neutral	Yes	Yes	No	Surprised	No	Communi-cation, facial expression and commands
L.C.	Surprised	Yes	Yes	He became very involved with the robot	Happy	He interacted and felt com-fortable	Communi-cation and interaction
D.K.	Surprised	Yes	Yes	No	Happy	He doubted and asked if N-MARIA was even a robot	Curiosity

Table 4. Mothers' answers during the second session.

Mothers' answers / Questions	**How do you think your child felt just before seeing the robot?**	**Do you think he/she liked seeing the robot?**	**Do you think he/she interacted well with the robot?**	**How do you think your child felt after seeing the robot?**	**Did your child have any unusual behavior with the robot?**	**What do you think the robot stimulated in your child?**	**Did you notice any difference in your child's behavior as the robot moved?**
D.O.	Neutral	Yes	Yes	Happy	No	Interacted well and obeyed the commands required	No
I.M.	Happy	Yes	Yes	Happy	He interacted well	Communi-cation	He became surprised
A.S.	Happy	Yes	Yes	Happy	No	Communi-cation and performed the activities	Curiosity about robot locomotion
L.C.	Happy	Yes	Yes	Happy	He had a productive interaction	He was cheerful, excited and communica-tive	No
D.K.	Happy	Yes	Yes	Happy	He manifested interest in building cars	He showed interest in mechanics and robots	He focused on the robot's face whereas it moved

In relation to emotions possibly felt by the children during the sessions, reported by the mothers, Figure 9 shows an increased description of happiness during the tests, revealing the children's positive contact with the robot and their comfort and safety throughout the experiments.

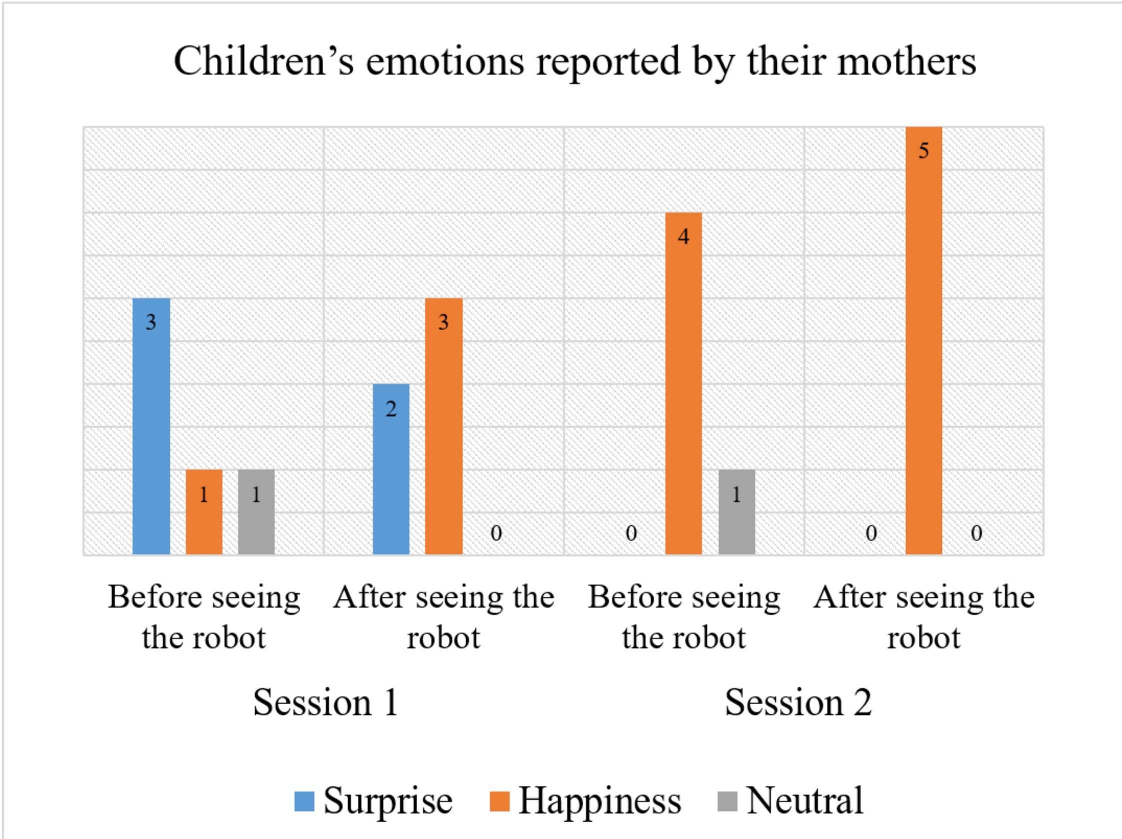

Figure 9. Emotions of five children reported by their mothers during two sessions. Happiness was growing throughout the experiments.

Professionals’ survey assessment

Table 5 shows the professionals’ answers who evaluated the usability of the robot, through three questions and the SUS scale. Regarding the robot’s usability, SUS had scores greater than 68 (average).

Table 5. Professionals’ answers who evaluated the usability of the robot N-MARIA.

Professionals / Questions	Do you think the robot could help with your sessions with children with ASD? Please explain.	What improvements do you suggest for the robot to be used in sessions as a therapeutic or pedagogical tool?	Please comment on your experience with the robot N-MARIA	SUS
Teacher	"Yes, I think. It would be an extra tool for interaction and communication"	"The professional could add necessary phrases and words for the child's daily life"	"It is very nice and makes us want to use it"	97.5
Teacher	"Yes, I think. it is a great alternative to help the children's pedagogical accompaniment"	"I suggest adding dialogue with differentiated interaction according to the selected emotions, adding a button on the therapist's tablet that confirms the sending of selected command"	"The robot is very attractive and interactive, however, it is necessary the greater stiffening of the structure to ensure a faster locomotion"	82.5
Occupational Therapist	"Yes, I think. I believe it would facilitate communication, interactions and responses to commands, which does not always happen"	"In the therapist's tablet, it is necessary to organize the dialogues in classes, such as: self-presentation, actions, objects and verbal reinforces, add a button of "Sent command" and put it in evidence"	"I thought the experience was great! She (N-MARIA) is very well worked out, both the program and the aesthetics. I believe it will be a very useful tool in the therapeutic sessions"	92,5
Psychologist	"Yes, I think. It could be a mediator of the therapist / child relationship, drawing attention and interacting in simple and direct ways. It could also stimulate emotional self-regulation in the children and develop interactive skills with themselves and with others"	"I suggest expanding the repertoire of speeches and objects"	"The experience was motivating and exciting. It is very useful as mediator for therapeutic and pedagogical activities with children"	100

Emotion classification and analysis

Figure 10 shows that the emotion “surprise” was the most detected from the classification analysis, for both baseline (before the child sees the robot) (Figure 10a and b) and test (after the child sees the robot) (Figure 10c and d), during the second session.

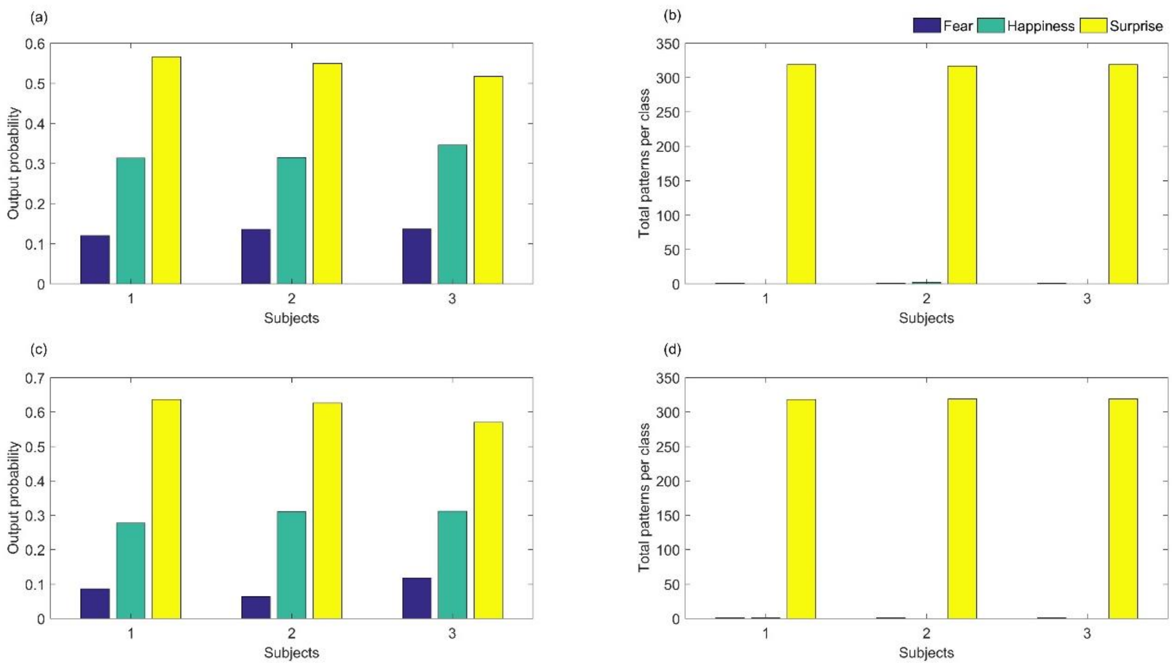

Figure 10. Profile of emotion classification for three emotions from three children with ASD: a) and b) correspond to the data from baseline moment, while c) and d) are data from test moments. Moreover, a) and c) present the probability of recognizing each known pattern.

Table 6 shows the brightness variations occurring in facial ROIs and all face of three children with ASD when they saw the robot during the second session in relation to the baseline (before they saw the robot). The values reveal significant temperature increases in all ROIs and the face.

Table 6. Values of brightness variations (BV) and p-values obtained from the facial ROIs when the child saw the robot.

ROIs	Right BV (*p*-value)	Left BV (*p*-value)
Forehead	10.87 ($p < 0.001$) ↑	10.44 ($p < 0.001$) ↑
Periorbital	9.58 ($p < 0.001$) ↑	10.17 ($p < 0.001$) ↑
Cheeks	9.68 ($p < 0.001$) ↑	11.69 ($p < 0.001$) ↑
Perinasal	11.94 ($p < 0.001$) ↑	10.84 ($p < 0.001$) ↑
Chin	10.64 ($p < 0.001$) ↑	11.73 ($p < 0.001$) ↑
Nose	12.60 ($p < 0.001$) ↑	
Face	10.93 ($p < 0.001$) ↑	

P-value < 0.05: significant brightness variation

"↑" indicates brightness increase or temperature increase

Discussion and Conclusions

This work introduced the social robot N-MARIA, which can be considered as a tool to evoke social stimuli and provide support for pedagogical tasks with children with ASD. N-MARIA corroborates with the Assistive Technology scenario, which aims to develop and use increasingly simple, accessible and useful gears for individuals with disabilities and professionals of the area (Beyer & Perry, 2013).

The robotic interface presented here provided support for the stimulus of social skills in children with ASD, such as shown through the results. N-MARIA may allow the inclusion of lessons or games chosen by the therapist for the process of teaching and learning, being characterized as a dynamic tool able to assist therapies with these children. Studies suggest that the integration of robots into recognized therapies, such as in ABA (Applied Behavior Analysis), could have clinical utility, therefore the investigation of benefits of robots as agents in therapies is considered relevant (Diehl et al., 2012). In this context, the children are received in a playfully, directed and personalized therapy with the robot.

The current study aimed at the assessment of the acceptability and usability of the social robot N-MARIA as a mediator potential tool for behavioral and pedagogical therapies. The acceptability of the social robot by the children with ASD, and the social interaction cues, such as eye gaze, tactile interaction and communication and other skills, such as proxemics and response to commands, were all considered in this study. The results showed a promising children-with-ASD and robot interaction. Moreover, this interaction was evaluated by the mothers who watched the sessions, and the robot usability was evaluated by professional, such as was shown in Tables 3, 4 and 5. These results are considered quite useful and valuable for the evaluation of the robot as a potential tool and mediator for therapies with children with ASD.

It is worth citing that N-MARIA was previously evaluated by typically developing children, aged between 8 and 12 years, who reported that they liked to interact with N-MARIA and also liked its functions, shape and face. Most of them said the robot was beautiful, reflecting a promising interaction with the robot, which also was useful to stimulate positive emotions in these children (Goulart et al, 2019(b)).

The robot N-MARIA acted as a mediator in the interaction with the children with ASD and the researchers (see Figure 8) and allowed an easy and fast access to its control interface along the two sessions. Mediation between robot and children with ASD and other people is widely cited in literature, such as the works using the robot Pleo (Kim et al., 2013), Keepon (Kozima et al., 2009), KASPAR (Costa et al., 2015), Ono (Zubrycki & Granosik, 2016), NAO (Suzuki & Lee, 2017), among others. However, for the robot to be a real interactive bridge with other people, it must have mechanisms (such as friendly structure, soft components and dynamic expressions), in order to be accepted by the children, providing interest, comfort and safety to them, also considering that children with ASD can react negatively in situations that are not usual for them (Cabibihan et al., 2013; Costa et al., 2015; Ben Robins, Ferrari, et al., 2010; Wong & Zhong, 2016). The robot must also be accepted by the therapists, who need of the increase of the interaction with these children for an effective application of their pedagogical activities (Zubrycki & Granosik, 2016). Thus, taking into account the acceptability of the robot N-MARIA by the children with ASD of our study, their experience in the first interaction was decisive for the success of the following sessions. Therefore, in this work, the robot stood stopped in the first session in a familiarization process to avoid fear situations that could generate phobias, unsafety or discomfort in the children (Costa et al., 2015).

The results of this work showed interesting findings during two sessions with the robot N-MARIA. Studies indicate that eye contact is limited during social interactions in ASD (Bal et al., 2010; Speer, Cook, McMahon, & Clark, 2007), but our results have demonstrated enough eye contact with the robot during the second session in relation to the first one, in general (Figure 4). Moreover, the number of eye contact with the researcher was basically higher during the sessions, being more expressive in the second session than in the first one, in general (Figure 5). In the opposite, the work of (Costa et al., 2015) cited the decrease of eye gaze towards the robot and an increase of eye gaze towards the researcher throughout sessions. Considerable numbers of eye contact with the researcher during the sessions could be a way that the child sought to feel safe and confident in an unusual situation. Then, taking into account the eye gaze towards the researcher in this work, examples can be mentioned when the child gazed the researcher, showing interest in something and seeking approval or consent during the tasks. Obviously, more sessions are necessary to verify the trend of the eye gaze throughout the sessions.

The tactile interaction was more spontaneously performed on the robot’s arms and hands in the second session (Figure 6), which are according to our previous findings (Goulart et al., 2018; Valadão et al., 2016) during a single session. N-MARIA’s arms are fully flexible, and its hands are soft and fluffy. These features may have contributed to greater manipulation of the robot by children. For two children, tactile interaction was greater during the first session (Figure 4), in which the touches were encouraged by the researcher, such as also found out by (Costa et al., 2015). Moreover, Figure 6 showed a higher number of areas touched during the first session. In this session, joint attention (Dawson et al., 2004; Klin et al., 2003) between the child and the researcher was performed when the latter pointed the robot’s body parts to the former, and both touched the robot together. In addition, tactile interaction was directly related to the child's proximity in relation to the robot, making easier the touches. In fact, the children predominantly occupied the intimate and personal areas around the robot, especially during the second session, demonstrating to feel more self-confident and safer in relation to it and the environment.

Results also showed that the robot was efficient to stimulate verbal communication, accomplishing the commands (Tables 1 and 2). Moreover, additional findings were relative to the robot's emotion recognition, as all children associated correctly the emoticons with the robot's expressions during the first session; imitation, as all they imitated the robot's emotional expressions in both sessions; shared engagement with the experimenter, when the children held spontaneously the N-MARIA's hands to walk together; and response to robot's commands repeated by the researcher to encourage the child, especially when N-MARIA asked or invited the child who did not answer or reacted, but when the researcher repeated the question or invitation, the child responded.

During the second session, emotion analysis was performed for three children with ASD, revealing significant temperature increase in all ROIs and total face (Table 5). The higher probability of emotion felt by these children was predominantly surprise, according to Figure 10. This result is different to the mothers' reports, who indicated predominant happiness. For our knowledge, there are scarce studies on emotion recognition using IRTI in children (with and without ASD) aged between 8 and 12 years.

In general, in the literature, a temperature decrease is observed for negative emotions mainly in adults, according to (Nakanishi & Imai-Matsumura, 2008). Temperature decrease is caused by sympathetic responses that trigger subcutaneous vasoconstriction or perspiration featured by the absorption of heat by perspiration pore activation (Ioannou et al., 2014; Kosonogov et al., 2017; Shastri, Papadakis, Tsiamyrtzis, Bass, & Pavlidis, 2012). In relation to the emotions considered in this work (surprise, happiness and fear), it is worth commenting that in our previous work (Goulart et al., 2019(a)), significant temperature decreases were found in the forehead for “surprise”, in the perinasal region for “happiness”, in the periorbital region and chin regions for “surprise” and “happiness”, and in the nose for “fear” and “happiness”, in typically developing children aged between 7 and 11 years.

Nose is especially noticed in literature as an indicator of stress and negative emotions with temperature decrease, which can also be present during startle and happiness (Cruz-Albarran, Benitez-Rangel, Osornio-Rios, & Morales-Hernandez, 2017; Ioannou et al., 2016, 2014; Kosonogov et al., 2017). Temperature decrease was also detected in the nose of children (aged between 19 and 42 months) during distress situation of guilt (Ioannou et al., 2013).

However, a significant temperature increase in the nose was detected for surprise in our previous work (Goulart et al., 2019(a)). Moreover, in that work, brightness variation showed significant thermal increases in the nose and chin in typically developing children, aged between 8 and 12 years, who were subjected to the interaction with the robot N-MARIA, which was also used as the emotional stimulus for those children (Goulart et al., 2019(b)). The thermal increases detected in the children of this study is supposed to be related to the increment in their heart rate, which generates a temperature increase, triggering a vasodilation in the face, such as suggested by (Ioannou et al., 2016), or a greater blood supply in the face coming from the facial muscle movements performed during the facial expressions, produced by the excitement of seeing the robot, according to (Wang et al., 2010). This excitation state was present in all children in the interaction with the robot, which may have contributed to the significant increases of the body temperature reflected in the faces of the children, such as measured by IRTI.

Although IRTI is an unobtrusive and efficient technique for evaluating emotions (Cruz-Albarran et al., 2017; Ioannou et al., 2013, 2014; Kosonogov et al., 2017; Salazar-López et al., 2015), a greater number of experiments and children are needed to prove the temperature variations (temperature increment or decrement) in the face of the children with ASD of our study.

The main limitations of this work consist of the small number of children with ASD analyzed during two sessions. Actually, a great difficulty was found to recruit children that fall within our inclusion criteria. In addition, it was not easy to deal with the spontaneity of these children to collaborate with the experiments. On the other hand, other works have also mentioned the limited number of children (Costa et al., 2015; Christiane Goulart et al., 2018; Valadão et al., 2016; Warren et al., 2015). In addition, the number of sessions was also small, characterizing experimental results. However, the analyses conducted in this study were considered very important to verify the acceptance of our social robot by the children with ASD, in addition to its ease of usage and the improvements of hardware and software that should be implemented in the robot, in order to enable future tests by more professionals in the ASD field. Thus, conducting longitudinal studies is intended by our research group.

Another limitation of this study is related to the large size of the robot, which hinders its transport. However, as a social robot for interaction with children, its size is suitable, as its height is similar to the children's height at the age considered in this study, such as also commented by (Cabibihan et al., 2013). Nonetheless, a new robot design with a smaller size can be elaborated, making the robot more portable.

Other limitation was observed in the sound emitted by the robot in relation to some object names in the pedagogical session, which caused doubts in the understanding by the children, due to the similarity of sounds. For example: comb in Portuguese is “pente”, but some children understood “dente” (tooth), and then they caught the toothbrush among the objects by its association with tooth, defaulting the correct selection of the object.

Regarding emotion analysis, although the manual ROI placing and checking necessaries on the face image in order to ensure appropriate frames for the analyses, interferences may have occurred, such as the action of the children in putting their hands on the their face, and sudden and fast head movements, which may not have been noticed in the checking process, but have modified the facial temperature.

The semiautomatic processing of place the ROIs is laborious for the selection of suitable image frames, in addition to mark and check the ROI positioning. Also, another limitation is the absence of a head tracking method, which could aid at the correct ROI placing during head movements.

In the context of the Assistive Technology, in which tools are needed to generate autonomy and improve the quality of life of people with disabilities (Huijnen et al., 2017), this work contributes to the evaluation of the usability and acceptability of the social and mediator robot developed, aiming at a simple and adaptable interface for diverse actions geared towards behavior and pedagogical therapies to be used with children with ASD. Moreover, the robot allowed the emotion analysis of these children in an unobtrusive way.

Anyway, more studies are needed, in order to make it useful for the guidance of future therapies with children with ASD.

Ethical approval: All procedures performed in this study involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

Informed consent: Informed consent was obtained from the parents' of all children included in the study.

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Conclusions

This thesis described three studies that were accomplished targeting the emotion analysis in children with ASD during the interaction with a social robot. Infrared thermal imaging was the unobtrusive technique chose to evaluate temperature variation for the emotional analysis. Difficulty in understanding and expressing emotions and sensitivity to touch in ASD were taken into account in this thesis.

In the first study, five emotions (happiness, sadness, fear, disgust and surprise), triggered by affective audio-visual stimuli, were evaluated in typically developing children, through facial temperature variation, by IRTI. A semiautomatic method relied on a manual ROI positioning and checking to evaluate the thermal variations in the facial ROIs. The results were promising, with a predominant thermal decrement in most ROIs for the emotions, the greatest emissivity variations induced by disgust, happiness and surprise, and a high accuracy (higher than 85%) obtained for the classification of the five emotions. IRTI showed to be a valuable touchless technique for emotion analysis.

In the second study, the emotional stimulus used was the social robot N-MARIA for the evaluation of three emotions (happiness, surprise and fear) in typically developing children. An automatic method of facial ROI positioning was proposed, based on an algorithm that detects faces in RGB cameras (Viola-Jones), which combined with the homography matrix, allowed such positioning on thermal images. The highest probabilities of emotions detected by the classification system were surprise and happiness, corroborating with the emotions felt reported by the children. In addition, a significant temperature increase was predominantly observed in the chin and nose, significant ROIs in thermal assessments for emotions. It was possible to infer the robot N-MARIA as a promising emotional stimulus able to trigger positive emotions in children.

In the third study, in which two sessions were carried out with children with ASD, social and pedagogical tasks were evaluated having the robot N-MARIA as a mediator. An emotional analysis was possible in the second session, in which the robot was the emotion stimulus to trigger happiness, surprise or fear. The usability of the social robot was evaluated by professional (teachers, occupational therapist and psychologist). The child-with-ASD-and-robot interaction was positive, in which children performed eye gaze with robot and the experimenter, tactile interaction, approximation towards the robot, communication and response to commands. Mothers reported favorable features during the interaction, as communication, curiosity, response to commands, positive interaction and happiness after their sons saw the robot. Professionals considered the robot as a potential tool able to aid in future therapies with children with ASD, by stimulating the interaction with the therapists, communication and aids in pedagogical accompaniment, in general. The usability of the robot reached score higher than 68 (average), based on SUS scale performed by the professionals. Regarding the analysis of emotions, significant brightness variations were found in all ROIs and the face, with a thermal increase. The classification system indicated the highest probability for surprise, in contrast to happiness reported by the mothers after theirs sons saw the robot.

Future Works

The thermal variation analysis through IRTI was demonstrated to be efficient, indicating significant variations in facial ROIs. The ROIs and emotions deserve attention in future studies with a higher number of children with ASD and an experimental protocol more robust, being assertive in identifying quantitative patterns for emotion recognition. In addition, the social robot can be used and evaluated in therapies for children with ASD by therapists, contributing to an effective assessment about its usability.

Social Responsibility

Some studies were performed at elementary schools from Vitoria. Our work stimulated and contributed to the creative process in the students, in the area of Assistive Technology and Robotics. Lectures on Assistive Technology and demonstrations of robotics were proposed and performed to students, as shown in Figure 14.

Figure 14. Lectures on Assistive Technology and demonstrations of robotics in elementary schools.

In another example, one of the schools (Éber Louzada Zippinotti), developed a “Knowledge Show” where one of the sections exhibited robots with different designs, names and functions made by its students (Figure 15), inspired by the lectures performed by the research group.

Figure 15. Exhibition of robots in “Knowledge Show” at school Éber Louzada Zippinotti.

Moreover, lectures on Assistive Technology were taught in events on Special Education promoted by the Federal Institute of Espirito Santo (IFES), in order to contribute to the knowledge and formation of students and professionals of the Education field.

Scientific publications

Journals

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Annex

A) Approval of the Ethics Committee of UFES

CENTRO DE CIÊNCIAS DA SAÚDE/UFES

PARECER CONSUBSTANCIADO DO CEP

DADOS DO PROJETO DE PESQUISA

Título da Pesquisa: RECONHECIMENTO DE EMOÇÕES DE CRIANÇAS COM AUTISMO ATRAVÉS DE EXPRESSÕES FACIAIS E IMAGENS TÉRMICAS DURANTE A INTERAÇÃO COM UM ROBÔ MÓVEL

Pesquisador: Christiane Mara Goulart

Área Temática:

Versão: 2

CAAE: 44899015.0.0000.5060

Instituição Proponente: Centro de Ciências da Saúde

Patrocinador Principal: Financiamento Próprio

DADOS DO PARECER

Número do Parecer: 1.121.638

Data da Relatoria: 24/06/2015

Apresentação do Projeto:

Trata-se de um projeto de pós-graduação em Biotecnologia. É um estudo transversal. Pesquisa observacional, cujo objetivo é avaliar sinais fisiológicos (expressões faciais e temperatura corporal) de crianças com Transtorno do Espectro do Autismo (TEA) para o estudo do reconhecimento de suas emoções durante a interação com um robô móvel. Será realizada com crianças com Transtorno do Espectro do Autismo (TEA), oriundas da Associação dos Amigos dos Autistas do Espírito Santo (AMAES), e crianças com típico desenvolvimento (TD), matriculadas na Escola Municipal de Ensino Fundamental Experimental de Vitória - Universidade Federal do Espírito Santo (EMEF-UFES), ambas com faixa etária entre 6 e 11 anos. O modelo de amostragem adotado para a pesquisa foi o de uma amostra aleatória composta por 2 grupos de crianças. O primeiro será um grupo composto por 30 crianças com TEA e o outro, por 30 crianças com TD, para análise de comparação.

Objetivo da Pesquisa:

Objetivo Primário:

Reconhecer emoções de crianças com TEA e com típico desenvolvimento (TD), através do registro de expressões faciais e variação da temperatura corporal manifestados durante a interação com um robô móvel. Além disso, analisar a interação da criança com o robô móvel e avaliá-lo como

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uma
ferramenta no desenvolvimento social de crianças com TEA.

Objetivo Secundário:

Captar as expressões faciais e a variação da temperatura corporal de crianças com TEA e com TD (típico desenvolvimento), para avaliação e reconhecimento dos seus estados emocionais.

Construir uma imagem lúdica amigável para caracterizar o robô móvel, de modo que desperte a atenção da criança com TEA e estimule-a à interação.

Propor um procedimento que permita interação entre a criança com TEA e o robô móvel.

Definir as habilidades sociais que serão avaliadas durante a interação com o robô.

Avaliar a interação criança-robô, utilizando a escala quantitativa: Goal Attainment Scaling - GAS.

Submeter o robô ao teste e avaliação pelos terapeutas que trabalham com as crianças com TEA, utilizando a escala System Usability Scale - SUS.

Avaliação dos Riscos e Benefícios:

De acordo com a pesquisadora, os riscos e benefícios são:

"Riscos:

Psicológicos: A imagem lúdica do robô pode não agradar a criança, desencadeando emoções negativas, como medo. Diante disso, todos os procedimentos experimentais serão acompanhados por um profissional de Psicologia e pelo terapeuta da criança. Físicos: Com relação ao robô móvel, se manuseado de forma imprópria pela criança, pode ocasionar leves escoriações na pele. Para evitar tal risco, o robô possuirá imagem lúdica composta por materiais leves e maleáveis, como Espuma Vinílica Acetinada (EVA), e a criança será acompanhada durante todo o procedimento experimental pelos pesquisadores e o terapeuta. Além disso, o robô se movimentará devagar e conterá dispositivos que garantam a integridade física da criança, como o Kinect, que localizará a posição da criança e proporcionará que o robô fique a uma distância mínima da criança, além de possuir um botão de segurança, que acionará a parada imediata do robô, se necessário.

Benefícios:

Compreensão das emoções expressas por crianças com TEA e estímulo às habilidades de interação social nessas crianças através da robótica móvel, para que desenvolvam um comportamento socialmente aceitável. Como um trabalho de pesquisa de pós-graduação, a contribuição é acrescentar aos meios científico e acadêmico um estudo de emoções de crianças com TEA, através da avaliação de sinais fisiológicos: atividade da musculatura facial e temperatura corporal em conjunto, uma vez que são poucas as pesquisas existentes nessa área. O robô poderá ser testado e avaliado pelos terapeutas das crianças, podendo contribuir, futuramente, com pais e profissionais como uma ferramenta que permitirá a melhor compreensão de emoções de crianças com TEA e estimulará o comportamento social das mesmas."

Os riscos e benefícios estão de acordo com o previsto na Res. CNS466/12.

Comentários e Considerações sobre a Pesquisa:

Pesquisa de relevância científica e social.

Considerações sobre os Termos de apresentação obrigatória:

Folha de rosto apresentada e assinada pelo reitor - adequada

Projeto Detalho apresentado

TCLE apresentado e adequado

Assentimento livre e esclarecido apresentado e adequado

Carta de anuência das instituições apresentadas

Recomendações:

Conclusões ou Pendências e Lista de Inadequações:

A pesquisadora adequou todas as pendências

Situação do Parecer:

Aprovado

Necessita Apreciação da CONEP:

Não

Considerações Finais a critério do CEP:

VITORIA, 24 de Junho de 2015

Assinado por:
Cinthia Furst Leroy Gomes Bueloni
(Coordenador)

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Appendix

A) Features of the children with ASD recruited.

General data						
1	**Name**	I.M.	D.O.	A.L.	L.C.	D.K.
2	**Age**	11	9	8	9	12
3	**Interview date**	June 25th 2018	June 26th 2018	June 27th 2018	July 25th 2018	July 26th 2018
4	**Birthday**	September 21st 2006	January 1st 2009	February 23th 2010	June 8th 2009	December 12th 2005
5	**Parents**	Mother (I.M.)	Mother (R.O.)	Mother (R.L.)	Mother (C.C.)	Mother (L.K.)
6	**Diagnosis date**	October 29th 2013	January 5th 2015	January 28th 2013	September 2012	July 14th 2008
7	**ASD level**	Mild/moderate	Mild (Asperger)	Mild/moderate	Mild (High Functioning)	Mild
8	**Height**	1.48 m	1.40 m	1.44 m	1.43 m	1.65 m
9	**Weight**	45 kg	35 kg	43 kg	31.9 kg	-
10	**Other neurological disorders**	No	No	No	No	Attention deficit and hyperactivity disorder
11	**Auditory impairment**	No	No	No	No	No
12	**Visual impairment (Glasses)**	No	No	No	No	No
Daily life data						
13	**Elementary school**	Sixth year	Fourth year	Third year	Third year	-
14	**Specialized services**	Pedagogical and neuropediatric accompaniment	Speech therapy and Educational psychology	Speech therapy, neuropediatric and nutritional monitoring	Speech therapy, neuropsychology and judo	Psychopedagogi-cal activities and occupational therapy
15	**Medicines**	Risperidone and sertraline (both 1 per night)	No	Risperidone (1.5mg per morning)	Risperidone (0.5mg per day) and atensine (0.150 per day)	No
16	**Allergies**	Allergic rhinitis	No	Asthma	Asthmatic bronchitis	Allergic rhinitis, dust and strong smells
17	**Food restriction**	No	No	No	Lactose	Lactose

18	**Feeding ((in)dependent)**	Independent	Independent	Independent	Independent	Independent
19	**Locomotion ((in)dependent)**	Independent	Independent	Independent	Independent	Independent
20	**Hygiene ((in)dependent)**	Independent in general (aid in brushing his teeth)	Independent generally	Independent in general (aid in oral care)	Independent	Independent
21	**Clothing ((in)dependent)**	Independent	Independent	Independent	Independent	Independent
22	**Favorite foods**	Pizza, salty snacks, noodle soup and gruel	Rice, beans, egg, cheese bread, French fries, strawberry biscuit	Apple, popcorn, rice and beans and juice	Banana, chocolate and mini breads with Nutella	*Paçoca*, cream biscuit, candy, soda
23	**Hated foods**	Vegetables and fruits	Corn and carrot	Soft food	Salad	Crisp foods, corn and cheese bread
24	**Favorite daily activities**	Games of cellphone and draw	Play with Lego, watch movies, go to the mall and draw	Play with clay and carts, ride bike, smart phone, watch movies	Play with dolls (super heroes and Monica's friends) and games with letters and numbers	Talk about cars, play games on the tablet and watch movies
25	**Hated daily activities**	Cut his nails, washi his hair and write	Organize his Legos	Physical education at school	-	Household tasks
26	**Use of computer, tablet or electronics**	Smart TV, tablet and smart phone	Smartphone, tablet and notebook	Smartphone, TV, tablet, computer	Smartphone, tablet and notebook	Smartphone, tablet and notebook
Behavior data						
27	**Humor ((un)stable)**	Stable	Stable	Unstable	Stable	Stable
28	**Aggression**	When he is angry or upset	No	When he is stopped in traffic or with noises	No	When he is angry or upset
29	**Depredation of objects**	No	No	No	No	No
30	**Stereotyped movements**	Open and close the hands	Shake the body when anxious (rarely)	Jump or balance his body	Shake hands	Touch the walls
31	**Reason for happiness**	Walk and draw	Lego	When he successfully performs a task	Number games, walk and	Play with young children

				and receives a compliment	chocolate ice cream	
32	**Reason for sadness**	Fly and receive household tasks	When other children take his Legos	When he is not understood or is far from whom he likes	When he is warned	When he is warned
33	**Things that catch attention**	Minecraft	Lego	Movies	Numbers and traffic signs	Cars
34	**How he express happiness**	He smiles and jumps	He smiles (Happy facial expression)	He tells he is happy and smiles	He smiles and tells	He talks to himself
35	**How he express sadness**	Serious facial expression and he cries	Sad facial expression	He grumbles and sad facial expression	He grumbles, gets angry and tells	He cries
36	**Exaggerated fear or phobia of anything**	Unknown situations	Dog and lizard	Darkness	Balloons and fireworks bursting	Fear of open windows and places
37	**Traumas experienced**	He got bad when his mother left home to work.	Dog attack	When he heard a teacher saying that he would not work with him because the child would not succeed	Balloons bursting	No
38	**Echolalia**	Yes	Yes	Yes	No	No
39	**Speak in third person**	No	Yes	Yes	Yes	No
40	**Touch sensitivity**	Yes (in the head mainly)	No	No	No	No
41	**Sensitivity to lights and sounds**	Yes	No	Yes (depending on intensity)	Loud noises	Sometimes, depending on intensity
42	**Other peculiar behaviors**	He manifests when he does not accept situations (ex.: He sits on the bus floor when there is no available seat)	He builds places and scenes with Lego	He laughs in every situation	Very easy to retain dates, numbers, letters and symbols. Great visual memory	He listens very well and sings
	Social interaction data					
43	**Acceptance of rules**	No (under blackmail)	Yes	Yes	Yes	Yes
44	**Understanding and response to commands**	Yes (depending on his interest)	Yes	Sometimes (he has difficulty in	Yes	When there is insistence

				understanding commands)		
45	**Eye gaze**	Yes	Sometimes	Yes	Yes	Little
46	**Verbal communication**	Yes (with living relatives)	He speaks little and with difficulty	Yes (simple words and answers)	Yes	Yes
47	**Nonverbal communication**	Pointing	Yes (he takes the person to the object of interest)	Pointing	No	No
48	**Imitation**	Yes (verbal expressions mainly)	Yes (cartoon dances)	Yes	Yes (he speeches of cartoons)	No
49	**Joint attention (appointment showing the object of interest)**	Yes (he points his likes received in the Internet and his games to his mother)	Yes (he also tells)	Yes	Yes	Yes
50	**Turn taking (participation and understanding of games in which each person has her/his turn to play)**	Not completely. He does not accept to lose and wants his turn to play soon.	Yes	He gets anxious in shared games	Yes	Yes