Ett system för affektiv beröring i humanoid och social robotik

A System for Affective Touch in Humanoid and Social Robotics

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A System for Affective Touch in Humanoid and Social Robotics

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A system for affective touch has been constructed, in a study of humanoid and social robotics. The system detects, processes and analyses signals from touch, identifies touch types, and provides a corresponding emotional response and expression. Touch is detected on an Epi humanoid robot head through the use of conductive paint on the inside on the head shell, and the electrical signal produced is processed into a digital representation of touch. Touch types are defined and classified through the application of machine learning. Approximate touches are applied to the head, including a variation in the areas of touch, and training provides a classification of ten touch types with an accuracy above 85%. Touch types are mapped to related emotional responses, providing the basis for the selection of an eye colour expression from an Epi humanoid robot. The system is integrated with the Ikaros cognitive modelling framework and real-time interaction is made possible, enabling a dynamical and complex human-robot interaction. This further confers a consistent framework for a future experimental evaluation of the system.

1 Introduction

The various modalities of communication are of fundamental importance in humanoid robotics, but the sense of touch has often been disregarded as part of the repertoire of a robot in social interaction. The application of theories and creation of models for this purpose, would be a contribution to humanoid and social robotics. This thesis is dedicated to the creation of a coherent model of touch interaction in humanoid and social robotics, involving the representation of touch and the categorisation of different touch types, where these are related to an affective response and a communicated expression. The model is tested through the construction of a somatosensory system that allows affective touch to become part of the cognitive architecture of a robot. The study aims at the implementation of such a system for affective touch through constructing a basic setup of the system that could be easily applied to a humanoid robot. This is done with the purpose of adding to the qualities of humanoid robots and for the development of touch interaction as an integral part of social robotics.

The system is initially conditioned by whether it is possible to achieve a functional detection of touch on the surface of a robot head, such that the signal produced can be processed and analysed to obtain applicable information from the detected touch. In the detection and identification of touch, different touch gestures, or touch types, are defined. The touch types are related to an affect and assumed to be conveying a meaning corresponding to that affect. A further condition for a functional system is if a relevant response to touch can be produced, where that response may be mediated by the emotions that are related to the types of touch involved in the interaction. Robotic expressions could comprise a communicated response, which is related to the emotional response. Therefore, the study employs a mapping of how emotions are related to touch, and of how a robot expression can be related to different emotions, establishing specific connections between the different representations of the system.

A system for affective touch should most generally aim at fulfilling the requirements for a meaningful human-computer bi-directional interaction, in that a robot should be able to "feel", "understand", and "respond", in ways similar, or analogous, to those of humans (van Erp & Toet, 2015). Human-robot interaction (HRI), including touch, can be said to be established if the robotic system is capable of *1)* spatial discernment, *2)*, discernment of touch types, *3)* providing an evaluation of the affective quality of touch and *4)* producing an expression related to the affective quality of touch. The system thereby created does not need not comprise functionality for touch that is identical to the human somatosensory system, but should produce a relevant representation and an effective behaviour that is similar to that of humans, and which acts as a foundation for functional interaction.

The measurement of an electrical field on the robot head shell surface can provide an input signal from touch, and from signal processing, data can be produced for the identification of touch. Signal processing here means a conversion of the signal from an analogue current to digital data and a treatment of that data to acquire information of which area has been touched, the strength of the signal produced, and the variation of the signal strength over time. This allows the creation of a representation of touch through cognitive modelling and the categorisation of touch into different touch types. A discrimination of different touch types can be carried out by use of machine learning, and the training of a machine learning model for the recognition of touch patterns. The detection and identification of touch thereby provides the basis for a robotic somatosensory system as analogous to the human sense of touch in the consequent grouping of sensory inputs into specific stimuli. The setup enables the detection of touch and the creation of a related electrical signal, the signal is processed as to extract relevant information, and a categorisation of touch is made possible through cognitive modelling.

Distinct neurophysiological pathways (Olausson et al.,

2002) for affective touch and a somatotopic mapping between tactile sensations and emotions (van Erp & Toet, 2015) may exist. Correspondingly, responses to touch interaction can be specific in kind and directly related to the type of touch that is applied, which is particularly relevant to HRI involving interpersonal touch. An over-arching mapping of affective touch to emotion would therefore enable the use of emotions as a response to touch. If robotic expressions can in turn be related to emotion, it would facilitate the identification of robot expressions to be used as a communicated response to touch. In the setup of this study, this corresponds to further cognitive modelling, where the representations of the different phenomena involved are related and set to provide an output of the system that confers a functional communication. This provides the grounds for bi-directional interaction, in which the application of touch to the robot affects the somatosensory system and a related expression is communicated to the human administering the touch. An integration of the system with the Ikaros cognitive modelling framework provides the possibility for real-time interaction with the robot, where responses can be experienced directly through robot expressions. This further increases the humanoid qualities of the robot, adding dynamics and complexity to the system for affective touch, and advances its abilities for social interaction.

2 Touch, Emotion and Robotics

The investigation of a somatosensory system in robotics relies on the basic features of touch, as established in physiology and neuroscience, human emotions as brought forth in primarily affective psychology, and the overall developments in robotics, including cognitive, humanoid and social robotics.

The Human Somatosensatory System

The sense of touch is an essential part of human biology and child development, and lays a foundation for how humans approach and experience the world. It is expended for the detection of, and orientation in, the environment, and touch is at the root of behaviours such as tool use and communication, as well as in the social creation of human culture (Field, 2001; Finnegan, 2014; Fulkerson, 2014). Touch communicates meaning as part of social function in humans and is an important part of social interaction and embodiment in communication (Dunbar & MacDonald, 1998).

Somatosensation provides humans with information of the environment through tactile perception, which provides an input in carrying out motor action. It enables the human embodiment of proprioception and the ability to discriminate external events from ones own actions. In humans, the sense of touch is processed in the primary somatosensory cortex, in the parietal lobe postcentral gyrus, which is somatotopically ordered, with neighbouring bodily areas corresponding to neighbouring brain regions, and in the adjacent secondary somatosensory cortex, important for distinguishing tactile shapes and detecting light touch (Banich & Compton, 2011; Gazzaniga et al., 2006). The human body contains multiple different somatosensory receptors that can be categorized into groups for contributing to the detection of pressure, temperature, vibration and can activate pain. Different parts of the body have different receptor densities, purveying different sensitivities to touch. Different receptor types have different mechanisms of activation, where the cells of receptors are involved in sensory transduction, which means that mechanical, thermal and chemical energy is converted into electrical signals, that become the input of the somatosensory system. Through neural adaptation and habitation learning, the somatosensory system can become less sensitive to its input or have increased sensitivity to lesser input. In providing the basis for proprioception and information of body position, somatosensation is at the foundation of the sense of embodiment and bodily awareness, including the localisation of limbs, and information from the somatosensory cortex is used by the motor cortex for the planning, control and execution of motor actions. Neural pathways from the somatosensory cortex provide information to the orbitofrontal cortex, which is responsible for important functionality with regard to social interaction, affect and reward, and interconnected with the amygdala, with a primary role in emotional responses, thereby relating touch to affective and interpersonal behaviours (Adolphs, 2009; Gazzaniga et al., 2006). The sense of touch may overall be considered foundational to social interaction and communication and the somatosensory system is an integral part in social cues and social coordination, as related through bodily actions and bodily awareness (Kolb et al., 2016).

Human Emotions

Affective psychology has yet to provide a consensus on the definition of emotions, but certain theories are established in their descriptions of components of emotional life. The theories of basic emotions which tend to be independent of factors such as cultural background, and that are exhibited by humans universally, is one such a description. The classification of such basic emotions differs between theories, where an agreement exists in that basic emotions involve distinctive neural pathways and characteristic physiological factors, and are related to characteristic universal nonverbal expressions, such as facial expressions. In the theory of basic emotions originated by Ekman and Friesen, emotions are classified from communication of facial expressions, where specific such expressions are universally recognised as conveying basic emotions (Ekman & Friesen, 1969; Ekman, 1999, 2004). The basic emotions may be grouped in multiple, but minimally five, emotions, where a grouping of six emotions usually includes happiness or enjoyment, surprise, sadness, anger, fear, and disgust. What may be referred to as complex emotions could in such a model be constructed as the combination of basic emotions, with a model of basic emotions thereby enabling a description of a more elaborate emotional life (Ekman & Cordaro, 2011; Ortony & Turner, 1990).

Whether emotions are perceived as pleasant, unpleasant or neutral is part of the characteristics of emotions in the theories of basic emotions, and is made a fundamental differentiating factor in theories such as the pleasure-arousal-dominance (PAD) model. The PAD model for emotional states or temperament applies a division of emotion into the three dimensions of pleasure, arousal and dominance, where these are scaled from the polarities of pleasant-unpleasant, arousal-non-arousal and dominance-submissiveness, with a numerical representation of emotion along related scales (Mehrabian, 1996). Experiments on similar models typically rely on physiological and non-verbal indicators for the detection of emotional states (Mehrabian, 2007).

Affective Touch

Discriminative touch enables the basic transmission of somatosensory information, a differentiation of the characteristics touch stimuli, such as location and texture, and can contribute to information processing in communication (McGlone et al., 2014). Communication through touch confers the mediation or triggering of emotional states. In social interaction, touch and touch gestures can comprise components of affect and emotion, contain an emotional meaning and produce an emotional response, and such touch is referred to as affective. Non-verbal communication in humans includes prosody of voice, facial expressions, gestures by way of hand and body, and the direct interaction through touch. In humans, affective touch is a primary means for conveying emotions and emotional states (van Erp & Toet, 2015) and it is suggested that humans have a specialized neurophysiological system for affective touch alone, separate from the mechanisms of discriminative touch (Gordon et al., 2013; Olausson et al., 2002). Löken et al. (2009) proposes that a gentle stroke, which is administered at a velocity of 1-10 cm/s specifically stimulates the neural structures for affective touch that is perceived as pleasant.

Affective touch involves physical interaction and produces emotions that are necessary for social bonding. It is used for the purposes of achieving well-being and social connection and it is a part of the modulation of behaviour (von Mohr et al., 2017). The topography of touch is important in determining its interpretation, with meaning depending on the location of touch and the creation of touch patterns, over time. The social and affective meaning of touch is highly dependent on context and the relationships of the interacting parties. Here, the emotional bonds between the person administering and the person receiving touch plays a major role in governing which areas of the body are available, relevant and appropriate for touch, and which type of touch is deemed applicable on different areas (Suvilehto et al., 2015). Context may further be regarded a causal factor also in the perception of emotion, as comprising a socially constructed phenomena (Armon-Jones, 1985). In the modulation of behaviour, touch has widespread effects on social attitudes, psychological factors and to the perception of social agents and institutions (van Erp & Toet, 2015).

Cognitive, Humanoid and Social Robotics

The problem of perception is fundamental in cognitive robotics. Artificial intelligence has historically been concerned with problem solving and the construction of relevant representations for the execution of tasks. The problems of robotics may however require replacing a reliance on representation with parallel activities that are part of a direct interaction with the world, where perception and action are dependent on each other, and perception and reasoning are intertwined processes (Brooks, 1991).

Robotic systems are dependent on what perception and the type of environmental information that are considered relevant as part of their detection processes, where infrared sensors and cameras are examples of mechanisms for creating sensory inputs (Balkenius et al., 2008). A structure of robot behaviours may be described in terms of hierarchical layers, where for example the avoidance of obstacles and the creation of motor control and locomotion provide the basis for a robots orientation in the world. This can be followed by planning and the execution of actions as a response to external stimuli. An extension can occur in robot learning, where discrimination is applied to objects in the environment and through object recognition. In imitation or demonstration, the robot interacts with humans and adapts its behaviours accordingly (Mataric, 2000; Schaal et al., 1997).

A robot is referred to as humanoid when its design includes features and behaviours approaching those of human beings, where facial and bodily features, and behaviours including facial expressions, eye movements, gestures and pointing are of importance (Adams et al., 2000). In mirroring behaviours, human movements and expressions are tracked and replicated by the robot. Eye movements and tracking can enable a participation in gaze following, with the movements of the robot eyes following the human gaze, in joint attention, and a shared visual focus. Robot functions and behaviours can include speech synthesis and speech processing, which thus enable verbal communication as part of the robots repertoire. Models of verbal communication can include turn-taking, where the overlapping and breaks, as well as fails and fixes occurring in human dialog are integrated into the robots behaviour to enhance its communicative abilities. Humanoid robotics may overall be regarded an investigation of human cognition, in comprising the creation of models of cognition corresponding to that in humans (Atkeson et al., 2000).

The implementation of humanoid features means an increase in social interaction competence, and humanoid robotics in this way allows for the development of social robotics, in which social human-robot-interaction (HRI) is the central focus (Duffy, 2003). Cognitive robotics is also at the basis of social robotics in that the problem of perception is part of the adaptation that is made for a functional social interaction. The behaviour of regulation includes a processing of social cues, and can be applied for general social coordination, where a robot further adapts to a system of social rules. In the behaviour of intention movements the robots movement and expressions can occur in a response to the presence and actions of other social agents. This means that robot behaviours include the communication of the purpose of the robots actions to humans. Humanoid robots may interact through emotional expressions and humanoid features and behaviours can thereby make possible the creation of emotional bonds in HRI. In a vision of embodied cognition, perception is an integral part of social coordination, and social interaction should be considered in constructing cognitive models. Social robotics is in these respects a continuation of the investigation of human cognition, as well as directed towards constructing robots that are functional in different social roles (Feil-Seifer et al., 2007).

Robotics and Touch

Communication is multi-modal in comprising all types of perception, and takes on an embodied quality in the full expressions and interchanges of social interaction. The sense of touch is in this way essential in the development of humanoid and social robots, but it is often neglected. While haptic interfaces for computers has been the object of much recent development, tactile information is used as a primary sensory input for robots for social assistance, robots as companions, and robots for human learning, which typically are used in the care of children and the elderly (Feil-Seifer & Mataric, 2005; Leite et al., 2013; Limbu et al., 2013). Studies that are directed towards a general investigation of touch in robotics and human-robot-interaction can be found (Albini & Cannata, 2020; Cooney et al., 2012; Johnsson & Balkenius, 2011; Kerpa et al., 2003; Martinez-Hernandez et al., 2016; Stiehl et al., 2005), and studies of material and methods for the detection of touch (Dahiya, 2019; Gallagher et al., 2018; Zhang et al., 2017) exist, but these topics have yet not received an extended treatment in the literature on robotics.

The development of a somatosensory system could be a contribution to robotic interaction with the environment in general, where tactile information is used in the orientation of the robot, for adjustment of motor actions, in the regulation of actions, in the mirroring of human behaviour and in the communication of purpose in intention movement. In social interaction, an increased potential for acting as an embodied agent would change the relationship to humans in aspects of direct bodily interaction and multi-modal communication. Comprising touch as a part of the robots general repertoire would be an advancement in social robotics, in contributing to behaviours involving social cues and for social coordination. The interest perceived in interaction with a robot, and the assessment of robot behaviours by humans, depends on the abilities of the robot for perceptible touch interaction (van Erp & Toet, 2015). Social touch can further be said to enhance the humanoid qualities of a robot, it improves the communication of emotions, produces and maintains the relationship between social agents, where touch is also a mediator of friendship, and manifests social presence and the embodiment of actions as performed by an interacting party, thereby establishing a social relationship. The development of robot behaviours for affective touch and related emotional expressions would have the greatest impact on robots that are used for care, assistance, companionship and learning, conferring a general improvement of the quality of interaction.

3 Theoretical Framework

We will here consider the implications of including cognitive modelling of touch in a model for humanoid robotics, and which types of touch should be included in such a model, as well as investigate relation of touch to emotions and how expressions in a humanoid robot may be applied as response to affective touch.

Machine Learning

In constructing a system for affective touch, the discrimination of types of touch from sensory input could be carried out from different schemes, where machine learning would provide a differentiation of touch types through pattern recognition.

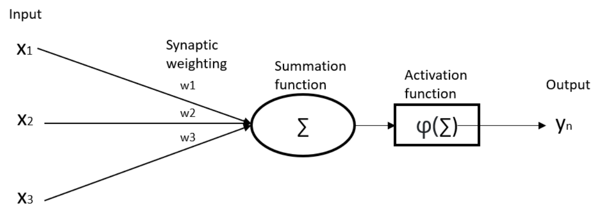

Figure 1: A schematic diagram describing the relationship between the inputs, x_i, synaptic weights, w_i, summation function, Σ, activation function φ, and output, y_i, of an artificial neuron.

Artificial neural networks (ANN) is a machine learning architecture that is inspired by the biological brain, and the mechanisms of the synaptic connections in the brain. Its architecture comprises a network of distributed parallel processing, in which a calculation is used for updating weights related to nodes in the network, analogously to how synaptic connections in the brain changes with neuronal signal input (see Fig. 1 for a schematic diagram of this process) (Zha, 2003). An ANN model thereby provides a classification of patterns or a regression of series, and the ability for producing an accurate classification can be established through the training of the network. In the categorisation of affective touch, such a model could be implemented as part of a cognitive model for the identification of touch, and used for the discrimination of touch types.

The artificial neuron is the basic processing unit of each artificial neural network, where nodes are connected to other nodes in layers of input, output and hidden layers, which are the layers between input and output. An activation function is applied for enabling a non-linear transformation of the input, which is necessary for complex learning. For the establishment of a neural network, two or more artificial neurons must be joined, where a basic architecture is the feed-forward neural network, for which the information is channelled in the forward direction, from the input nodes, through the hidden layers, to the output nodes. This is referred to as a static architecture, whereas ANN architectures involving cycles or feedback loops between nodes, or that employ various delays to the processing, are called dynamic structures. A neu-

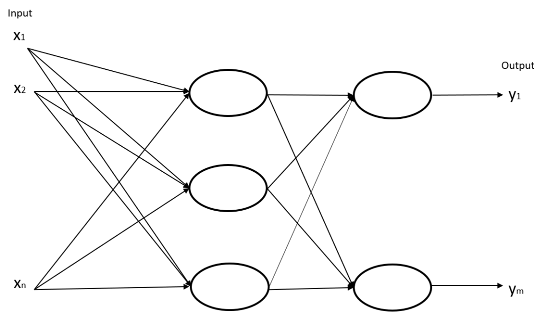

Figure 2: Schematic diagram describing the setting of input values, x_i, and the production of output values, y_i, and the connections to nodes hidden layers, of a multilayer neural network.

ral network may be described by the input nodes being in a direct connection with the output layer, in a single layer network. A multi-layer neural network is created by including hidden layers, that can be fully or partially connected, where fully connected layers are referred to as dense layers (see Fig. 2). In so-called back-propagation, a calculation of gradient descent is executed, where the gradient of the error produced by the model is used to update the node weights and the bias of the network in order to reduce the error of prediction. In such a gradient calculation, a step of gradient descent towards an optimum is made, in a process that can be repeated until the network converges on such an optimum.

The classification provided by the ANN is produced by the detection of characteristics in data and the generation of a corresponding pattern recognition, which in turn produces a potential for predictive processing. The learning process of an ANN is accumulative in adapting to patterns of information, where the parallel processing architecture permits a fast computation, when implemented on a standard computer. In supervised learning, a mapping of input and output is used, where the neural network is provided with the target response for the given inputs, and the relation between the pattern and the target value determine the setting of node weights. In unsupervised learning, target values are not used, but the characteristics of the inputs are differentiated as part of the learning process and used as a basis for classification (Wong & Hsu, 2006). In reinforcement learning, there is neither a given target response, nor is unsupervised learning applied, but the learning is optimised through the maximisation of a reward function, which determines which outcome corresponds to a successful recognition.

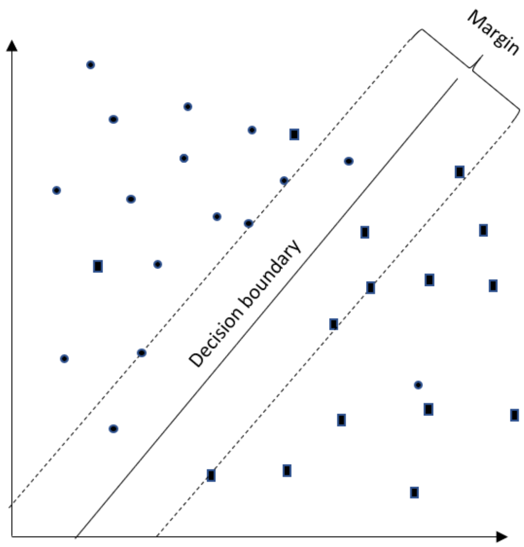

Figure 3: Illustration of decision plane and margin and the differentiation of classification instances (filled circles and squares) in two dimensions.

Machine learning can further be provided by a support-vector machine (SVM). The idea of the SVM is derived from the structural risk minimization principle (Vapnik, 1995). It functions through the transformation of data into a higher dimensional space R^N, with a number of features, *N*, where a decision boundary and hyperplanes within a certain range of that boundary are set to differentiate data into classes (Gandhi, 2018). With a parameterisation of N=2, the hyperplane is one-dimensional and for N=3, it is two-dimensional, with a hyperplane separating data into two classes (see Fig. 3). The margin, which spans the space between the decision boundary and the instances of data in training, separates the classes and should be maximised. A total separation of data into different classes may however prove impossible and does typically not provide an effective optimisation. In soft margin classification, the SVM therefore weighs the widest possible margin in maximisation against the possible misclassification of data in the process of differentiation. Support vectors are the instances of data that are situated on the border of the margin and these vectors correspond to the designation of the decision boundary. The support vectors are used as instances representative of the classification of data and these instances are applied in the computation of prediction. For nonlinear datasets, kernels can be used for implicit mapping of inputs into high-dimensional feature spaces. The kernel represents the transformation of the decision boundary into an appropriate form for separating the classes.

It has been proposed that the classification and regression of an SVM can become superior to that of an ANN, independent of coding (Wong & Hsu, 2006). It is possible that the optimisation of an SVM has less complications due to the sparse parameterisation in defining the classifier, where an ANN uses an undetermined combination of connection weights for its recognition. The calculations of the SVM may also be less computationally intensive (Gandhi, 2018). Specifically for touch patterns, the treatment of direction in movement may be more suited to SVM learning (Lau et al., 2008)

The Communication of Affective Touch

Approaching affective touch in humanoid and social robotics, it is assumed that different touch types will tend to communicate a specific meaning, and that a discrimination between emotions conveyed by affective touch is possible. Emotions may be communicated through touch, face and voice expressions, with partly differentiated neuroanatomical systems, that can converge into an emotional representation (Schirmer & Adolphs, 2017). It may also be produced by touch independent of face and voice. Hertenstein et al. (2006), describes a study where one participant touches the arm of another, without them having visual or auditory access to each other, and attempts to communicate an emotion. Such touch is sufficient to communicate the six basic emotions, where the person being touched makes a relevant decoding of that touch, among twelve possible choices, with an accuracy of 30-38% for happiness, 24% for surprise, 31-35% for sadness, 57-59 % for anger, 48-51% for fear and 63-83% for disgust. It is possible also for observers of such touch to decode the involved emotions, where participants in the study watched video clips of the first part of the experiment and judged which emotions were communicated. Observers could distinguish the emotions involved in affective touch, with a probability above chance for emotions happiness, anger, fear and disgust. In a follow-up study, Hertenstein et al. (2009), emotions were communicated via touch applied to the whole body, with an overall increased accuracy in their categorisation, compared to touching the arm only. The duration of touches that can communicate emotions in these studies tend to vary from 4.5 to 8 seconds, with slight differences in duration between the studies. In Thompson and Hampton (2011), the communication of emotions through touch is investigated with regard to the relationship of the involved parties. Here, two strangers can communicate and discriminate six basic emotions, among twelve possible choices, from touch, with a success of communication that has a mean of 39%. In romantic couples this ability increased, where surprise and sadness, with the lowest recognition in strangers, is at an approximate level of the other emotions and the mean is raised to 52%.

The Duration and Intensity of Emotion

In order to gain a dynamic representation of emotions in humanoid and social robotics, a description of how emotions arise, change and expire, and which intensity they are perceived to possess is needed. As emotions unfold over time, the qualities of emotions are in complex relationship to a multitude of factors. The duration of emotions tend to be dependent on affective style, including factors of attention and regulation. In a simple model of emotion, emotions may however be said to have a peak of intensity and a recovery period, in which the emotional perturbation is lessened and returns to baseline. Emotional responses can in this way differ by peak and amplitude (Davidson, 1998). The rise time to the peak and the length of the recovery period of the emotion is dependent on the individual. The variation of emotional duration may overall be large, where emotions can last a few seconds, or remain for multiple hours. If emotions are regarded as dynamical processes, the duration and intensity of an emotion could be dependent on the nature of the event triggering it, the properties of the emotion itself and the characteristics of the subject experiencing the emotion (Verduyn et al., 2015; Verduyn et al., 2012). Disturbances in the balance of emotional dynamics, where multiple peaks of emotion can occur, the recovery period is lengthened and the emotion sustained over longer periods of time, is symptomatic of mental disorders, occurring in for example major depression disorder and generalised anxiety disorder (Deckert et al., 2020).

Basic emotions tend to arise and subside relatively quickly, where unpleasant basic emotions arise faster and have longer recovery periods than pleasant ones (Ekman, 2004). Studies on the duration and intensity of emotion further show that among the unpleasant emotions, episodes of sadness tend to be most intense and last the longest, followed by anger, with fear having a lower intensity and shorter duration than anger, and disgust having both the lowest intensity and shortest duration (Brans & Verduyn, 2014). Enjoyment, as a pleasant emotion, has a shorter duration than all of the unpleasant emotions (Verduyn et al., 2009), and surprise differs from the other basic emotions in an overall considerably shorter duration (Ekman, 2004).

Colour and Emotion

The communication of emotions in humanoid robotics can be carried out through features such as facial expressions, speech and sound and motor action. The Epi humanoid robot includes expressions mediated through the colour of the robot eyes, which we will employ for the communication of emotion. Colour may be considered emotionally salient, where the dependence of emotion on colour is complex, and relies on many different factors. Emotional reactions to colour are overall dependent on contextual, historical, environmental, physiological, psychological and cognitive factors and depends on individual characteristics.

A review of the literature on how colour is perceived as an emotional expression, has been undertaken, where different such expressions could be related to specific emotional states. According to Valdez and Mehrabian (1994), and in terms of the Pleasure-Arousal-Dominance (PAD) model (Mehrabian, 1996), colour hues red and yellow, with high wavelengths, are both physiologically and emotionally related to arousal, whereas blue and green, with low wave-length, are emotionally calming. An increased saturation, as related to brightness and relative perception of white, tends to be correlated with increased arousal. Red and yellow are here conceived as unpleasant, where blue and green are pleasant, depending also on saturation and brightness, and where increased saturation and in particular brightness is associated with pleasure. The findings may be only weakly generalisable, and with a dependence on both gender and culture. Fugate and Franco (2019) describes a study on english-speakers, where participants are asked which colour they relate to the words for basic and other emotions. Here, happiness is related to yellow and light blue, sadness to dark blue, anger is related to red, followed by black, fear is related to black, followed by red and disgust is related to shades of green and brown.

Häring et al. (2011) combines eye colour with bodily movements and sound as a humanoid expression of the Nao robot, investigating whether different combinations of these expressions may produce the emotions joy, sadness, anger or fear, in human research subjects. Eye colour is chosen based on cultural preferences, where red is associated with anger, dark violet with sadness, yellow with joy and dark green with fear. An effect is in this study noticed in how the colour red contributes to the expression of anger. In Terada et al. (2012), basic emotions are represented by coloured light from an acrylic sphere. Joy is represented by bright yellow-red and green, surprise by yellow-red, sadness by blue-purple, anger by red, fear by purple and blue, and disgust by red-purple and blue-purple. This setup was used in an experiment in which research subjects related and rated the colours as expressions of emotion. The results from this study provides some support for the representation of emotion through colour, according to the arrangement described. Tärning et al. (2019) represents basic emotions through coloured lighting of the eyes in the Epi humanoid robot. An experiment is conducted in which its participants evaluate what basic emotions these colours represent. Turquoise is rated highest for enjoyment, closely followed by violet, blue and yellow, with red clearly rated lowest for this emotion. Turquoise is rated highest for surprise, followed by neutral (grey), green, yellow, with an overall lower rating for blue, and with red distinctly being rated the lowest. For sadness, blue is rated highest among the colours, followed by turquoise, and with a smaller difference between turquoise and the other colours. Red is here clearly rated highest for anger, and also to a lesser extent represents disgust, where the evaluation of the other colours is grouped without distinct separation. A succinct separation of colours is not found for fear.

These studies suggest that the display of different colours may contribute to or elicit emotionally specific reactions from human subjects. The representation of emotions through the use of colour in humanoid robots is however not unambiguous and may to an extent be arbitrary, where complexities such as the meaning and effects of displaying a changing or dynamic combination of colours has not generally been investigated. The studies available however suggest that an overall tendency of differentiated emotional responses to specific colours exists.

4 Setup, Implementation and Results

A somatosensory system has been constructed for detecting, processing, analysing and responding to touch on a humanoid robot head, in an investigation of affective touch in humanoid and social robotics. In this section, the setup of the system will be described. This includes the materials used, the Ikaros modelling platform, which provides a basis for cognitive modelling, the methods used for the detection and identification of touch and the implementation of machine learning for classification of touch types. Results from the training of machine learning models for the recognition of touch patterns are presented. This is followed by the motivation for the possible responses of the system and how they are implemented into the system. This implementation relies on the mapping of touch types to emotions and expressions, which will be discussed and the parameters for the setup of this cognitive modelling program will be described. The material design of the robot head, and the construction of the setup for producing an electrical signal from the detection of touch, is further elaborated in Johansson et al. (2021).

The Epi Humanoid Robot

The Epi humanoid robot comprises an open humanoid platform for developmental robotics, with a design and features that can be used in a study of affective touch in robotics. It is constructed by Johansson et al. (2020), and made available for this study by the Lund University Cognitive Robotics group. The study was performed on an Epi head shell, in plastic material, with a design that allowed its production from 3D printing. In order to optimise the setup, there was a successive development and testing of the material, the components and their connections within the system, as further described in Johansson et al. (2021). The Epi humanoid robot is directly compatible with the Ikaros cognitive modelling framework, which is integrated with the system of this study (Balkenius et al., 2020).

The Ikaros Cognitive Modelling Framework

Ikaros is a programming framework for cognitive modelling that has been instigated by the Lund University Cognitive Science robotics group (Balkenius et al., 2020). It is primarily directed towards the simulation of system-level brain and neurological functions, where different functionalities can be tested through the application of input data. A cognitive model may be regarded a simulation of a cognitive system, and of how information is processed by this system. In Ikaros, the effects of cognitive modelling on the data may be studied, in an investigation of the corresponding neurological processes. The Ikaros program is further directed towards the control of robots, where the modelling of cognitive systems can be interfaced with robotic functionality. The Epi humanoid robot can be directly interfaced with the existing functionality of the system, meaning that robot actions and expressions can be related to cognitive processing (Johansson et al., 2020).

The Ikaros program is based on self-retained modules of C++ code, with a particular functionality, where these modules can be connected through the module inputs and outputs. The inputs and outputs are defined trough the use of XML protocols describing the data type and size of the connections. This creates a structure of functionality and connections between different functionalities, thus making it possible for different such functionality to be used in conjunction and dependent on each other. The structure enables the processing of information in real-time, with a flow of information between modules, as well as to and from external processes.

An integration of Ikaros with the somatosensory system, with the creation of Ikaros modules for the identification of, and responses to touch, would mean that the system could be related to different Epi expressions and actions. These include changes to the colour hue and intensity of the eyes, changes in pupil size and position, body position and motor actions through e.g. a tilt of the head, and auditory expressions produced from sound synthesis. These features can be used in a response from Epi, where different touch types may produce a related Epi expression. A WebUI graphical interface acts as display for the streams of data, and the results of cognitive modelling. It includes a representation of the Epi head, with a graphical presentation of its expressions, including a display of different eye colours. With a module for the identification of touch connected to the input of a module for response and the production of expressions, the latter could be connected to the Ikaros WebUI or Epi robot. Cognitive modelling of touch and related responses can then take place in real-time, in a direct interaction with the environment, where the system for affective touch facilitates a bi-directional exchange with humans.

The Detection of Touch

For the detection of touch, conductive paint is applied to the inside of the surface of the Epi humanoid robot head shell. Conductive paint is easily utilised, allows detection of touch over large surfaces, its implementation is economically cheap and the design is easily replicated on similar robot bodies. The conductive paint acts as a potentiometer sensor, facilitating a capacitance measurement. When a conductive material, such as a human hand, approaches or is applied to the surface, its electrical field produces a change in capacitance of the conductive paint area. Capacitance is proportional to the charge of an area relative to its electrical potential.

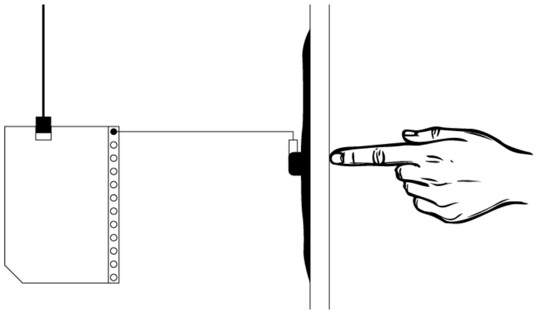

Figure 4: Illustration of the principal setup for the detection and signal processing of touch. The capacitance of an area of conductive paint changes and the electrical signal of the area is directed through cords to an Arduino touch board

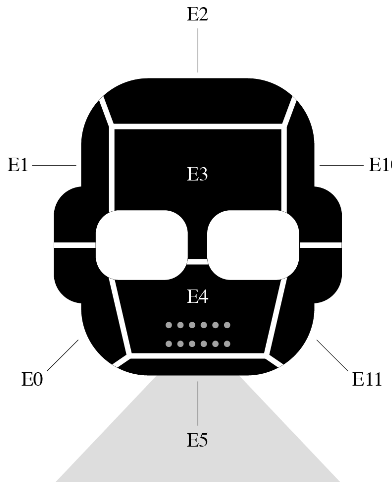

Figure 5: Illustration of the topography of sensor areas, with the related electrode indicated, in the front of the Epi head shell.

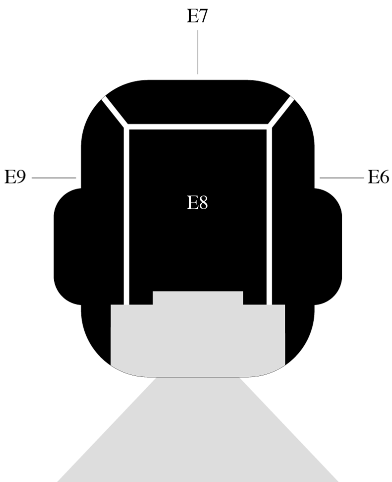

Figure 6: Illustration of the topography of sensor areas, with the related electrode indicated, in the back of the Epi head shell.

The conductive paint is divided into twelve areas, where each of the areas is connected to one of the twelve electrodes on an Arduino touch board. The touch board has twelve corresponding electrode sensors, and performs the initial processing of the electrical signal in the system (see Fig. 4). The topography of the different areas, in the front and back of the inside of the head shell are shown in Fig. 5 and Fig. 6. Each sensory area is connected to an electrode of the touch board, which processes the electrical signal created from touch, so that it can form the basis of further analysis. Furthermore, the electrical field of a hand that is placed only in the proximity of the head can produce a limited electrical signal from the capacative areas. The electrical fields of surrounding conducting objects may also be detected by the sensors, and the production of a signal from this, or from for example the movement of arms or the body of an interacting human, in the proximity of the Epi head, will be regarded as noise in the system constructed. Therefore, a filter is further imposed on the signal, through the signal processing of the touch board, as a cut-off against noise.

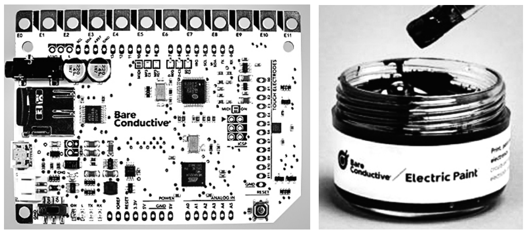

Figure 7: The Arduino touch board and conductive paint from Bare Conductive.

In this study, Bare Conductive's Electric Paint (Bare Conductive, n.d.) was used as conductive paint, with Bare Conductive's Touch Board (Bare Conductive, n.d.) employing an Arduino Leonardo mini-computer, which comprises a ATmega32U4 microcontroller (Bare Conductive, 2020), was used for signal processing (see Fig. 7). The touch board consists of 12 electrodes (denoted E0-E11), where the signal of each electrode provides the input of an MPR121 capacative touch sensor, providing analog-to-digital conversion. The touch board has a serial output for both receiving and transmitting data, as accessed through a USB protocol. Modifications of the signal processing can be carried out using the standard Arduino IDE. The output of the data produced is transmitted through connecting a micro USB cable from the board to the USB port of a standard PC computer.

Signal Processing

With the detection of touch from multiple sensory areas and an electrical signal providing information of the characteristics of touch, patterns of touch may be established, during a certain time frame. The initial representation of touch comes from this measurement, and consists of the values of the electrical signal produced and their changes over time. The signals of the sensor areas provide information on which area is touched and the electrical field detected, through the changes in capacitance occurring when charge is added to the area. These factors are dependent on the surface of the hand that is in contact with the detector over time, and on the movement of the hand, in time.

The Touch Board uses an MPR121 capacitive sensor to digitise the capacitive signal. The integrated circuit charges and discharges the capacitance with a known current during a specific time step. The current produced is proportional to capacitance and the area measured over time, wherefore a linear ramp voltage is induced. The linear ramp voltage is filtered and output as a 10-bit digital value, which represents the voltage reached during the charge time, with a maximum value of 3.3 V and where a voltage of zero implies that it did not exceed the minimum value of approximately 3 mV, in that time.

As the measurement of capacitance depends on the total charge of an area, a hand touching the head will tend to contribute to the increase in charge to a larger extent with an increased pressure of touch, and therefore the measurement of touch may be correlated to the pressure applied, where pressure is force per unit area. Furthermore, the electrical field of the hand producing a signal from other areas in the proximity of that area which it is closest to, could be used as a measurement of the location of the hand, beyond the localisation of the hand on the area that produces the largest signal.

In the detection of an electrical field, the capacitance measured may differ due to effects of the environment, where for example the electronics of a robot head, or close-by conductors can produce an electrical field interfering with the detection. In the signal processing of this study, a baseline signal is therefore first defined for all electrodes and the value of this baseline is subtracted from the total measured value, where their difference, δ, may be considered a measurement of the differentiation of the signal from the baseline. If δ is below a certain cut-off, the value of the measurement is set to zero in order to discard noise and interference. The signal thereby takes on values ranging from δ to u_{max}, where u_{max}, is the maximum value. For the identification of touch, the signal values are normalised by factoring them with $\frac{1}{u_{max}}$.

The sample rate of the signal processing is set to $\sim$28 Hz providing a reasonable resolution for the measurement of the duration and timing of touch. The resolution in time is theoretically 0.035 s, where effects from the charging and discharging of the capacitance of the electrodes may affect the measurement of one such time step. In the system for touch, touch patterns are measured during a time window of a maximum of seven seconds. This measurement has two hundred time steps for each of the twelve electrode measurements, thus comprising a total of 2400 measurement values.

Touch Types

In this study we will assume that social touch has the characteristic of consisting of patterns and gestures of certain generality and varying complexity. A further assumption is that it is possible to discriminate between and recognise different touches, in that different touch types have specific connotations, convey meaning and communicate an affect. Definitions of touch gestures and types tend to vary in the available literature, but common categorizations do exist. From related research, and with primary sources of the study of affective touch in Hertenstein et al. (2006) and Thompson and Hampton (2011), and the classification used in the recognition of touch patterns of Alonso-Martín et al. (2017), Cooney et al. (2012), Huisman (2017), Sun et al. (2017), and van Wingerden et al. (2014). Different touch types were compiled and included in this study according to the extent that they occurred in the literature and depending on their rele-

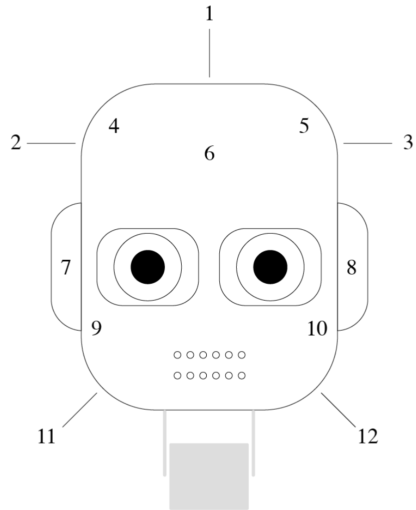

Figure 8: Approximate areas for touch on the Epi humanoid robot head.

Touch	Definition	Areas
None	Effects of background and random interaction.	All
Short touch		
Tap	Quick and gentle touch with one or multiple fingers.	P:9,10 S:7,8,11,12
Poke	Quick jab or prod with one finger.	P:6 S:4,5
Press	Brief prod with multiple fingers.	P:6, S:4:5
Slap	Quick hit with the fingers or the flat of the hand.	P:9,10 S:7,8
Long touch		
Pat	Repeated and quick prods, with the fingers or the flat of the hand.	P:1 S:2,3
Pick	Repeated and quick prods, with one finger.	P:4,5 S:6,1
Hold	Sustained grasping performed with one hand.	P:7+9+11, 8+10+12 S:4+7+9, 5+8+10
Stroke	Directed movement with the fingers or the flat of the hand.	P:5→10,4→9 S:10→5,9→4
Rub	Repeated back and forth movement with the fingers or the flat of the hand.	P:4,5 S:6,1

Areas is the area on the Epi head, as illustrated in Fig. 8, where P denotes the primary areas, and S denotes the secondary areas.

Table 1: The names and definitions of touch types, with the areas for the application of touch given.

vance to the study. The definitions chosen are directed towards basic affective touch under the condition that the touch is applicable to a humanoid robot head with non-elastic skin in a stationary setup. In creating an overview of touch types, differently named touch types with the same definition of execution were considered the same and thus merged under one name. Touches specifically involving a location were considered generally, so that e.g. "stroke cheek" is considered a "stroke", and "rub back" is used as "rub". Touch types such as "shake", "lift", "squeeze", "twist", "tickle" or "scratch", were not considered valid and meaningful in the application on a robot head shell, nor inviting a straightforward execution in a possible experiment involving research subjects applying touch to the robot.

In the creation of such a nomenclature, the different touch types should have distinguishing characteristics, but it is also possible that the combination of different types of touch could comprise a more complex, but yet relevant communication through touch gestures. The touch types should thereby describe basic components of touch communication, that combined can be considered to convey further meaning and communicate affect. We also distinguish between characteristically short and long touches, where short touches are more basic in nature, and where the long touches have patterns that are additionally dependent on time. The short touches may correspond to the beginning parts of long touches and the long touches can overall comprise parts that correspond to short touches. The long touches may also be considered part of a continuum, where the characteristics of one touch could provide a foundation for, or be a part, of the characteristics of other types.

Nine different touch types were thereby defined. The short touches are: "tap", in which there is quick and gentle contact of one or multiple fingers with the touch object, "poke", where a finger is used in a quick prodding action, "press", involving multiple fingers performing a brief pushing action, and "slap", in which the hand is flattened and the fingers or the hand is used in a quick hitting action. The long touches are: "pat", where the hand is flattened and the fingers or the hand repeatedly and with short intervals quickly prod the object, "pick", in which a finger repeatedly and with short intervals quickly prods the object, "hold", where the touch object is grasped and held by one hand in a sustained action, "stroke", where the fingers or the hand are in contact with the touch object while performing a movement along it and "rub", in which the hand is flattened and the fingers or the hand is in contact with the touch object while performing a back and forth movement on it. In order to include a possibility for other interaction to occur, a touch type referred to as "none" is further included. It will primarily be related to signals produced from background interference and interaction patterns that may be deemed random or accidental. It will also represent a misidentification of touch, in that the other touch types are not forced to include badly defined patterns, making the prediction certainty a more meaningful quantity by including the possibility of an interaction outside of the defined types for affective touch. The touch types and their definitions are compiled in Table 1.

Examples of how short touches may be considered a part of longer ones here includes how a "tap", "press" or "slap" may be the beginning of a "pat", "hold", "stroke", or "rub", in the approach of the hand to the touch object. These short touches could also be components in the repeated prodding of a "pat". A "poke" may be be the beginning of a "pick", and a "pick" could consist of repeated "pokes" with short intervals. The characteristics of long touches could for example be related in how the "pat" and "pick" both comprise patterns of repeated touches and may interchange, or in how the sustained trait of a "hold" could provide the foundation of, or be part of a "stroke" or a "rub", where "stroke" and "rub" both comprise movement.

In the literature, the location of touch is sometimes given or indicated, but is overall not clearly defined and related to specific touch types. We have therefore defined primary areas of touch, for the different touch types, according to the definitions in the literature reviewed, where possible and relevant, but generally for being a probable location of execution and to provide a reasonable placing for the application of the touch type to the humanoid head. Secondary areas of touch were chosen as the relevant and applicable neighbouring areas of the primary ones, where the "stroke" motion is reversed in the secondary case. The primary and secondary areas for the different touch types are listed under *Areas* in Table 1, where Fig. 8 shows the numbers, from 1 to 12, assigned to the different areas of the Epi robot head. It should be noted that these areas describe the location and movement of touch and are not identical to the conductive paint areas on the inside of the head, used for the detection of touch (see Fig. 5 and Fig. 6).

The Identification of Touch

In the setup of the system for affective touch, the signal produced from the detection of touch provides the input to the touch board where it is converted and processed, as to produce data for the identification of touch. The output from the touch board is used as input for the Ikaros program, to further analyse the signal and to enable the cognitive modelling of a somatosensory system. The installation of Ikaros was done on a Linux platform, and the Arduino board was connected through a USB port to a standard computer running Ikaros. To create a suitable treatment of the signal in correspondence to affective touch, four new modules in Ikaros have been developed (Karlsson, 2021). The different stages of processing and analysis, with a division between these modules, is illustrated in Fig. 9.

The continuous output from the touch board provides a stream comprising the signal from detection, and a first module in Ikaros constitutes an interface, between the USB port and Ikaros, which is compatible with the serialisation and format of the output from the touch board and the USB protocol. In the module, the input is formatted appropriately and the data can through the output of the module be supplied to other Ikaros modules. The output stream of the module consists of an array with the values of the signal for each time-step, where one row of data comprises the twelve values measured by the electrode. The values represent the strength of the signal from the detection of touch, which is set to zero when there is no triggering of touch above the noise level in the

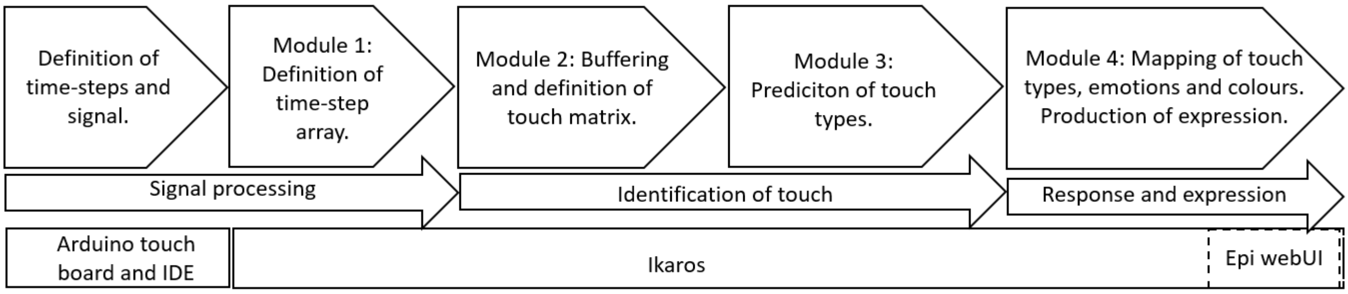

Figure 9: Illustration of the stages and general chronology of the system for affective touch. In the inital signal processing of the touch board, the time-steps and signal are defined. In the first Ikaros module an array for time-steps is defined, followed by the identification of touch through the buffering and definition of a matrix for touch over a time window, in the second module and the prediction of touch types from the defined touch, in the third module. The fourth module is dedicated to the response and expressions of the system, where touch type certainties are factored with emotion strength ratios and the result is mapped to colours, and an Epi eye colour expression is produced.

touch board signal processing.

The array of each time step of the first module provides the input of the second module, which enables the basic identification of touch. The signal values during an interval of the ten latest time-steps will be referred to as a buffer. The buffer provides a sample of the signal produced during that time, and a summation of the signal values of each buffer is used to determine whether a new touch has started and whether it is ending. The start and end of a touch is defined by imposing a condition on this sum to be above or below a certain level. When the condition for the start of a touch i fulfilled, a possible time window of seven seconds is started, where arrays from the interface module are added to a two-dimensional matrix, with rows representing time steps, and with the columns containing the signal values for each time-step. The gathering of data for the identification of touch can end when the buffer condition is fulfilled, or when the time-window reaches it end. If the gathering ends due to the buffer condition, zero values are added to remaining matrix of the time window, as to always provide an equally sized matrix, whereupon the time window ends before the full seven seconds have been concluded. A short touch will thereby tend to produce an matrix of initial values above zero, followed by a larger interval of zero values. A longer touch may also end before the conclusion of the time window, with the adding of zero values for the remaining rows. If a touch is applied during the full time window, and continues beyond it, a re-triggering of a new time-window will tend to occur, as the first time-window ends. The matrix thereby produced represents a measurement of touch, and its values may be regarded as the identification of a touch pattern, that can be used for machine learning classification.

For machine learning from an artificial neural network (ANN) in Ikaros, a library from the Tensorflow platform, for machine learning algorithms and related implementations, is used (Martin Abadi et al., 2015). The basic structure of the ANN comprises a sequential model with input, output and two hidden dense layers, where each node connects to all nodes in the adjacent layer. The input is adapted to the format of the identification matrix, of 2400 places, and the hidden layers consist of 256 and 32 nodes each. The number of outputs in an ANN classification task are set to the number of classifiers, which here corresponds to the ten different touch types. A batch normalization layer is applied after the first dense layer, fixing the medium and variance values for further inputs and preventing over-learning. A drop-out layer is employed after the second dense layer, to prevent over-learning, increasing the generalisation of the learning, by randomly setting node weights to zero. In order to add higher dimensions and enable a more complex prediction of patterns, an activation function is applied to the computation of the dense layer weights. The activation function of dense layers in our model is *relu*, which stands for rectified linear unit, which handles negative gradient values in computation, conferring advantages such as efficiency and improved quality of gradient descent calculations. For the output layer, a *softmax* function, which is a normalised exponential function, is used. When the value of the output is determined, a loss function calculates whether the arrived values are close to or differ from the expected value. If a value differs significantly from the expected value, this is an indication that the network calculation of weights and bias should confer an adjustment to improve pattern recognition. The *Adam* optimisation algorithm is therefore applied to the learning, with the learning rate set to 0.01, for further promoting efficiency and reducing noise.

The Scikit-learn library for machine learning was employed for the application of a Support Vector Machine in this study (Pedregosa et al., 2011). The effectiveness of an SVM depends on the selection of the kernel, the kernels coefficient γ, which is set to prevent overlearning, and the soft margin parameter C, which sets the boundaries within which risk minimisation are applied to a hinge-loss function, used for determining whether the calculation should be adjusted. The SVM model employed in this study is non-linear and uses a Radical Basis Function (RBF) kernel, which is applied for overcoming the space complexity problem of memory usage, by using support vectors in training, rather than accessing the full data set. The parameter C could be considered a regularisation parameter in the SVM, where a a smaller margin may be accepted with a larger value of C, dependent on if the decision function provides a better classification of all training points. A lower C will tend to lead to a larger margin and therefore a more plainly applicable decision function, but however potentially reduces training accuracy. In this study, the parameter is set to a relatively high value, C=*100*, where accuracy of classification is emphasized, compared to a maximisation of the margin of the decision function. The RBF kernel coefficient γ parameter defines the impact that a single training example can have on the classification, where lower values of γ confers a possibility for larger such effects and higher values of γ will mean the imposition of greater restrictions. The γ parameter is inversely related to the radius of influence of the samples selected by the model as support vectors. The model of this study employs a setting of γ=1, with a relatively restrictive scaling, imposing a comparative limitation on the effects of training data on classification. An SVM employs feature weights in the representation of the hyperplane, and our model here uses the scheme of balanced weights, where there is an automatic adjustment of weights depending on, and inversely proportional to, the frequency of the different classes in the classification input.

The system thereby comprises a cognitive model for the identification of touch, where a matrix representing touch is created and machine learning is used for the recognition of touch types. The certainty of prediction is defined as the relative probability of the prediction being true, and it is given directly by the machine learning model. The output of the prediction module in Ikaros is the certainty values for all touch types. This allows for a categorisation of touch to be carried out and a possibility of recognising which touch type a particular touch is. With the identification process integrated in the Ikaros framework, the predictions of touch can be applied in real-time, making the categorisation of affective touch in a direct interaction with an Epi robot possible.

Training and Accuracy

Touch areas	N.o. touches	Accuracy (ANN)	Accuracy (SVM)
Primary	1000	0.90	0.88
Secondary	1000	0.87	0.87
Total	2000	0.86	0.88

Table 2: For the data samples from primary areas, secondary areas and in total, the number of touches applied and the accuracy produced in ANN and SVM machine learning, respectively.

For training, touches of different types are applied to the Epi head, where the matrix of time-steps and signal values that is produced in the identification of touch, is used as the input for learning. In the supervised learning applied, a target label is used for relating the touch pattern to a particular touch type, and provided as input for classification. The different touch types are applied in a approximate fashion, according to the description of Table 1, and each touch type is repeated multiple times, producing samples of data that can be used in the machine learning training of a model. The data is divided into training, test and validation samples, according to best practice, so that 70% of the data set is used for the training of the model, 15% is used for validation of training, and 15% is used for testing the model and producing an evaluation measured through accuracy and loss. Training is executed through the functionality of the machine learning frameworks and the validation of the training provides an estimate of how classification is thereby developed. With learning over epochs, turns of fitting the data, a recognition of patterns may be established and an increase in the training and validation accuracy and a decrease in the training and validation loss, will tend to occur. Testing is then carried out, where an overall evaluation of accuracy and loss can be provided from the test data. The SVM model did not allow a division into validation and test data, and the test sample was used for both the learning and the evaluation, which should be noted in comparing the test accuracy of the ANN and SVM models.

The short touches were applied with a duration of approximately 0.5-1.5 s, and the long touches were applied with a duration of approximately 1.5-4.5 s. Two different samples of data, with regard to the touches applied, were gathered, where the first contains a sample of touches that were applied to the primary areas, and the second contains a sample of touches that are applied to the secondary areas, as described in Table 1. The samples are of the size of 1000 touches each, for the primary and secondary areas respectively, totalling 2000 touches, which are distributed equally over the different touch types, with 200 touches applied for each touch type. The "none" touches are created by lowering the buffer threshold for a touch to start and moving hands and arms in the vicinity of the head, with the system thereby detecting what may be considered by-products of touch interaction, occuring as a background to the execution of touch.

As presented in Table 2, the learning from the primary area touch sample, produces a test accuracy of approximately 0.90 for the ANN, and the SVM gains an accuracy of 0.88. The learning from the secondary touch area data produces a test accuracy of approximately 0.87 for the ANN and with the same value of accuracy for the SVM. When merging the two samples, and thereby gaining a sample of 2000 touches on both primary and secondary areas, the test accuracy is 0.86 for the ANN, and 0.88 for the SVM. Thus it appears that the effect of mixing touch areas, to the extent done in this study, so far only has a marginal effect on the accuracy of learning in the classification of touch types, and that learning can occur where different touch areas coincide between touch types. A differentiation of touch characteristics can thereby be upheld also in a varying application of touches. Further, notable differences between the ANN and SVM accuracy can not be observed, indicating that the different models share classification and that learning is optimised across models. The comparison of model accuracies is a cross-check also for the effects of changing and adding touch areas to the analysis. The fact that neither model shows a markedly lowered accuracy as a result of this, implies that a reasonable classification of the data from touches on varied touch areas is not provided by coincidence.

Mapping of Touch and Emotion

A test study, described in Johansson et al. (2021), was made to establish a relationship between basic emotions and the touch types defined. Forty participants of an online survey were shown a recorded video of different touch

	Enjoyment	Surprise	Sadness	Anger	Fear	Disgust
Tap	**0.61**	0.00	0.08	0.31	0.37	0.15
Poke	0.01	0.45	0.19	**0.59**	0.28	0.29
Press	0.00	0.43	0.22	**0.56**	0.47	0.36
Slap	0.00	0.63	0.45	**0.89**	0.60	0.41
Pat	**0.40**	0.38	0.21	0.29	0.18	0.16
Pick	0.03	**0.65**	0.19	0.46	0.31	0.31
Hold	**0.61**	0.58	0.16	0.16	0.34	0.14
Stroke	**0.73**	0.38	0.28	0.01	0.05	0.08
Rub	**0.63**	0.29	0.21	0.05	0.10	0.06

The scale for strength were set from values *None* (0.0), *Weak* (0.5) and *Strong* (1.0).
Shading of emotional strength is applied as: [0.0-0.2], [0.2-0.4], [0.4-0.6], [0.6-0.8], [0.8-1.0]
The strongest emotion related to a touch types is set to **bold**.

Table 3: Table of expected emotional responses from touch, with the mean strength of the emotion given as a fraction corresponding to the mean value assigned to it. Shading is applied to the table for an overview, where a darker shade indicates a stronger emotional response and a lighter shade a weaker emotional response

types being applied on an Epi robot head and asked to provide a judgement on which of the six basic emotions they would expect to constitute an emotional response to that touch. The scale for emotional strength ranged from 0.0, for the choice of "none", meaning no emotional response, to 1.0, for the choice of "strong", a generally strong reaction, where a value of 0.5 is defined as corresponding to the answer "weak". The results of this study on the mapping of touch-emotion are presented in Table 3. For every touch, the expected triggered emotion and the mean strength assigned to it, are shown. It can be observed from this table that enjoyment has a relatively high representation among the emotions selected, and that anger and surprise are also often considered expected emotions to be triggered from touch. Sadness, fear and disgust are less commonly related to the touch types defined, but a "slap" includes a higher strength for sadness and fear in its response, and a "press" is evaluated as triggering fear with a strength of 0.47.

Mapping of Emotion and Colour

With basis in the literature, as previously described, a mapping of colour to emotion has been defined, as to provide robotic response in the form of Epi eye colour expressions. The six basic emotions are here represented by an expression of colours distributed over colour space and related to distinct colour characteristics. A differentiation has been made between primarily enjoyment, which tends to be a pleasant emotion, and secondarily surprise, which may be neither pleasant nor unpleasant, to the other emotions, sadness, anger, fear and disgust, which tend to contain a larger unpleasant component. Enjoyment and surprise are mapped with a higher brightness, and closer to the RGB value of white, (255,255,255), while the unpleasant emotions will tend to have comparatively lower brightness and be closer to black, which has an RGB value of (0,0,0). As a default colour we have chosen middle grey, with an RGB value of (119,119,119), which will act as a centre to the expressions produced, and to which the colour expression will return when there is no emotional response.

Emotion	Colour	RGB
Enjoyment	Turquoise	(64,224,208)
Surprise	Gossamer green	(48,144,127)
Sadness	Midnight blue	(25,25,112)
Anger	Venetian red	(200,8,21)
Fear	Tyrian purple	(94,8,68)
Disgust	Cactus green	(92,117,94)

Table 4: The mapping of emotion to colour. For each basic emotion, the conventional colour name and corresponding RGB values are noted.

In this study, turquoise will be mapped to enjoyment, gossamer green is mapped to surprise, midnight blue to sadness, venetian red to anger, tyrian purple to fear and cactus green to disgust. In Table 4 the colours and the corresponding RGB values are noted. The RGB model is additive in that it allows for the creation of new colours through the addition of RGB values. Colour may in this way be combined from a division in colour space, where the colour characteristics are retained relative to their inclusion in the combined result. This means that emotions can be represented by a combination of colours, where the representation of an emotion is proportional to the strength of that emotion. The expressions produced by the system could in this way be regarded as representing complex emotions.

Response to Touch

For the treatment of the response to touch in the system, an additional, fourth, Ikaros module has been created (see Fig. 9, for an overview). The output from the identification of touch is an array consisting of ten columns with certainty values from the prediction provided, and these certainties are used as the input for the response module. The prediction certainties of the ten touch types then provides the basis for determining a relevant response. Taken as a summation of patterns, the set of certainty values may in total be considered an approximation of the touch applied, representing a combination of touches, where the different types are weighted according to their certainty value. Approaching the predictions in this way allows for the treatment of complex touch, where touch is comprised of the categorical touch types as basic elements, or where different types are applied successively during the duration of the time window.

In order to allow for responses also during the course of the time window, which can last up to seven seconds, the application of touch is divided into different stages. These stages are defined to depend on the buffer signal value and how this value changes. Buffering is carried out in the second Ikaros module, for the identification of touch. If the change in signal strength over the time of the buffer selection is a positive value, above a certain limit, i.e. the signal is increasing, the touch is defined to be in the "attack" stage, most likely in the beginning of a touch, where an increase in signal strength follows from the placing of the hand on the head. If the absolute value of change is below that limit, the application of touch is defined as being in a "sustain" stage, during which the hand is placed on the head, and not yet removed from it. If the value of the signal is negative, with an absolute value above the limit, this is regarded as the "release" stage of the movement, where the hand is pulling away from the head. Predictions are then possible when the stage of the signal changes from "attack" to "sustain", and a signal is first established, or from "sustain" to "release", where a fuller prediction can be made. With a release, it is likely that the touch is finished and the overall prediction is executed and the time window ended. It would be possible for a touch to contain many such phases however, where for example the repetitions of a "tap" or "pick" may be detected as changes between these stages. Predictions are made through the machine learning model of the third Ikaros module. By allowing for predictions to take place during the extension of the time window, it is possible to produce a more dynamic response, where expressions may be communicated before the application is fully finished, and dependent on the characteristics and touch components of the touch applied thus far. This gives the human party administering touch a continuous feed-back which allows the system to approach the qualities of real-time interaction further.

In producing a response, we will assume that touch should be mapped to emotions as a primary arbiter of such a response, where the values of Table 3, provides the relative representation of emotions related to touch types. The prediction certainty values for the different touch types are factored with the corresponding ratio representing the strength of an emotion, to produce values of relative emotional representation as a response to touch. The prediction certainties of the touch types identified from the touch applied, are thereby used as a weighting, representing a combination of touches and affecting the proportion of emotions that will comprise the emotional response. In the Ikaros module, a matrix of ten columns corresponding to touch types and six rows for emotions, are filled with values representing the resulting emotional response data, with the values of the strength of the six basic emotions weighted by prediction certainty according to their relation to touch.

In the system for affective touch, the colour of the Epi eyes is used as an expression, and in order to further produce an expression as the communication of a response, the emotional response must be mapped to that colour expression. Colour is in this study mapped to emotion, where different emotions correspond to a certain setup of RGB values, according to Table 4. Colour is here represented by values from the RGB model, in a combination of the red, green and blue colour hues. The RGB values corresponding to different basic emotions are factored by the relative values of the emotional state, where the combination of such values are normalised to the sum of relative values, to produce the RGB value of the combination.

The representation of emotions are weighted according to:

$$E_{Rep,j} = \sum_i C_{Touch,i} \cdot E_{Rat,j} \ , \tag{1}$$

where $E_{Rep,i}$ is the representation of emotion i, $C_{Touch,i}$ is the prediction certainty of touch type i, and $E_{Rat,j}$ is the strength ratio of emotion j, related to touch type i, where the different touch types, i, are summed over. The RGB value of an emotion is then set as:

$$\vec{E}_{RGB,j} = E_{Rep,j} \cdot \vec{E}_{RepRGB,j} \ , \tag{2}$$

where $\vec{E}_{RGB,j}$ is the weighted RGB value and $\vec{E}_{RepRGB,j}$ is the RGB value, of emotion j. The total RGB value of the expression is thereby given by:

$$\vec{E}_{TotRGB} = \sum_j \vec{E}_{RGB,j} \ , \tag{3}$$

by summing the RGB values of the different emotions, j, and the weighted emotions thereby contribute to a summed RGB value. The sum of RGB values is normalised to fit the RGB value range, so that expressions of colour are in this outline limited to the ranges of the RGB setup and the related colour space. The combination of colours according to this scheme, enables the production of an RGB value that depends on the relative representation of emotions, according to the touch-emotion mapping and dependent on the prediction certainties of the current touch types.

As to include a duration of emotions in the description of the response, and to make the responses further dynamical and temporally interactive, a simple and generalised function for the changes of emotional intensity with time is defined as:

$$\begin{cases} t < t_{peak}: \ A_{Emo,i} = a_{Emo,i} \cdot e^{\frac{(t-t_{peak})}{t_{peak}}} \\ t > t_{peak}: \ A_{Emo,i} = a_{Emo,i} \cdot e^{\frac{-(t-t_{peak})}{t_{peak}}} \end{cases} \quad (4)$$

where $A_{Emo,i}$ is the amplitude of emotion i, at time t, and $a_{Emo,i}$ is a factor of emotional amplitude that will is set for emotion i, and t_{peak} is a set time at which the peak in amplitude will be reached. The emotional intensity will hence describe an exponentially shaped rise, until it reaches its peak, where it decays towards zero. With different values set for $a_{Emo,i}$ the amplitude will be dampened to different extent, approximating the difference in intensity and duration of different emotions, i.

To further provide temporal complexity in the presentation of a response, functionality has been developed for the inclusion of a history of emotions as a basis for the production of an expression. This means that when a new emotional response occurs, a representation of the history of emotions are added to the emotions currently expressed, with relative values representing the distribution of emotions that have constituted the responses of the interaction thus far. The historical emotions are treated as a group, providing a background to the current emotion, where the values of emotional strength for this group becomes part of the calculation of an expression. As a group, the historical emotions will further have a duration and emotional intensity that is separate from the current emotions. With the possibility of including such a background, the real-time interaction expressions will comprise a merging of colours over time that is dependent on the previous interaction.

Parameterisation and WebUI

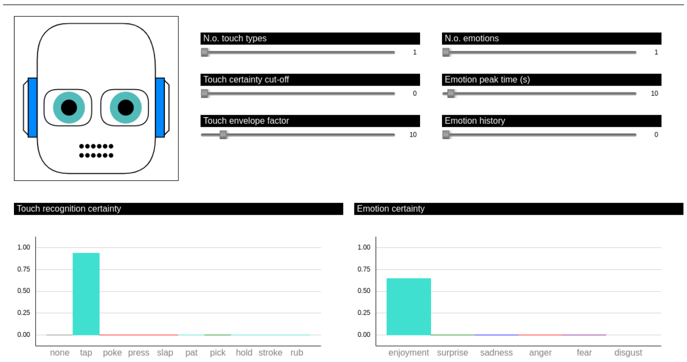

Figure 10: Screenshot from Ikaros WebUI for displaying an Epi response to touch. Parameters are set to default values, as visualised by the sliders in the upper middle and right, and a tap is detected, as seen in the lower left bar graph, with an enjoyment emotional response, as displayed through the lower right bar graph. An expression is produced, as shown by the above left Epi head graphic, which displays a turquoise colour of the eyes.

In the Ikaros response module, a parameterisation has been created for the number of touches that should be part of the further weighting of a response, so that it is possible to vary this value within the setup. A parameter is also related to prediction certainty, making possible a cut-off on the touch type certainty values, where touches with a certainty below that value should be excluded from factoring in the response. For the default setting, shown through the Ikaros WebUI in Fig. 10, there is a selection of one touch type, where the requirement on touch certainty is that it should be above zero. A further parameterisation is applied to the number of related emotions of each touch type, to be included in the factoring and used in the calculation of the colour expression, where the emotions are selected to be included according to the strength fraction, with higher values taking precedence. In the default setting, one emotion is selected, so that the primary emotion of the current touch types provides the basis for an expression only. Fig. 11 shows the

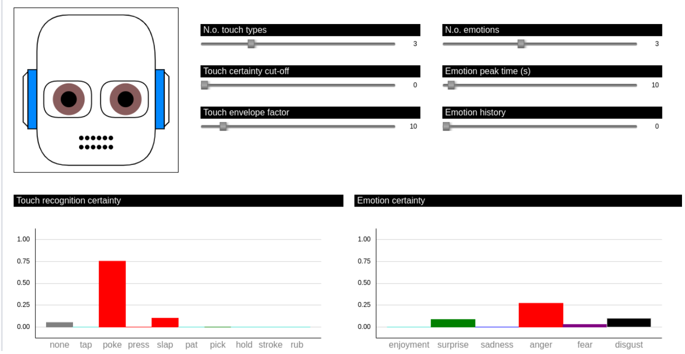

Figure 11: Screenshot from Ikaros WebUI for displaying an Epi response to touch. Parameters are set to select three touch types (slider in the upper middle). Primarily a poke, secondarily a slap, is detected and a none touch for background is also identified (lower left bar graph). An emotional response of anger, disgust and surprise, in that order of magnitude of strength, is produced (lower right bar graph). An expression of red-brown colour is produced by the merging of related colours in the eyes of the Epi head (above left).

WebUI from a parameterisation allowing three touches and three emotions to occur as a result of a touch. This means that the emotions, weighted from the touch certainty and the strengths of the emotions related to the different touch types, occur according to a normalised distribution of their relative representation. The RGB values corresponding to the emotions weighted by certainty thereby contribute to the expression in the form of Epi eye colour. In this way, an increase in the complexity of the identification, response and expression, is enabled, as multiple touch types and emotions contribute to the final expression.

To enable a further increase in complexity, the inclusion of an emotion history is also parameterised. The emotion history is by default excluded, but can be included to an amount dependent on the emotion history parameter. This parameter has a range from zero to one, where a value of zero means an exclusion of the history, and a value of one that the relative values of the emotion history contributes equally as the current touches in

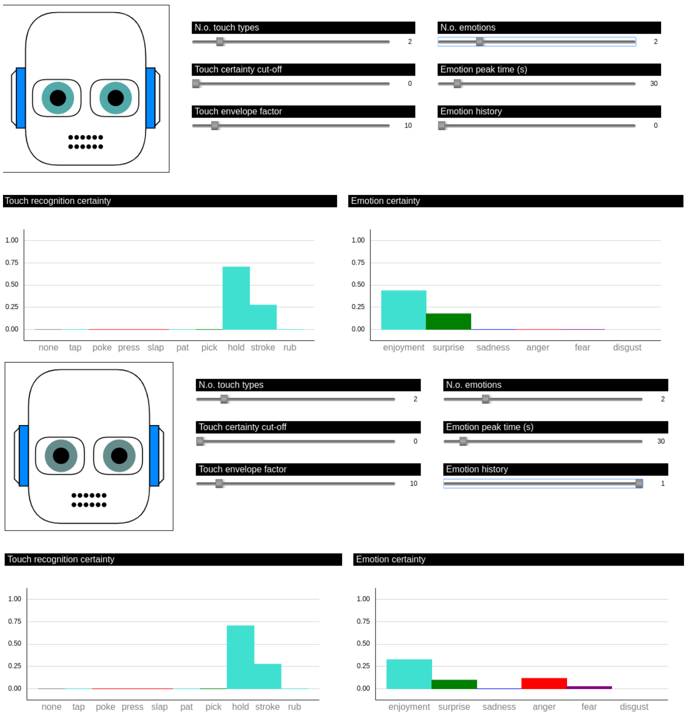

Figure 12: Screenshots from WebUI for displaying an Epi response to touch. Two possible touch types and two emotions are selected through the parameterisation, where a hold and stroke are identified. Above: The emotion history parameter is set to zero, and the response is a representation of the current emotions enjoyment and surprise, in that order of magnitude. Below: The emotion history parameter is set to one, and the response is a representation of the current emotions enjoyment and surprise, which are reduced compared to the when a history was not included, and with anger and fear added as specifically historical emotions.

the calculation of the colour expression. This is exemplified in Fig. 12, which shows the emotional representation without and with a history included. When the duration has passed the peak of intensity, the historical emotions tend to have a lower intensity than the current emotions, due to the intesnity having decreased for a longer time.

A parameter is defined for the touch envelope factor, which sets the level at which a new stage in the envelope of a touch occurs, among the different stages, "attack", "sustain" and "decay". This setting determines the initiation of predictions during the time window, where the envelope factor is multiplied with the general buffer size for triggering touch. The default value for the envelope factor is ten, meaning a change in signal value of ten times the buffer signal is used to set the limits of the different stages of touch. Setting this parameter to a value of one would in turn mean a triggering of different stages according to the triggering of the general touch identification, according to the buffer size. With an increase in the value of this parameter, less triggering of the stages of touch would tend to occur. Depending on this parameter, there will be a production of responses from the shifting of stages during the time window, and thus it is a setting affecting the temporal changes of the response and the dynamics of the expression.

Furthermore, the duration of emotions is adjusted by the emotion peak time parameter, which sets the time at which there is a peak in intensity of the emotional response. As previously described, this means that there will be an increase in intensity up to this point, and thereafter a decrease in intensity for the remaining duration. Changing this parameter changes the peak of intensity of all emotions, where this will have an effect on the changes in intensity of current emotions, and the merging of these into an expression. It will also correspond to changes in historical emotions, and their contribution to the expressions produced. The amplitude factor, for setting the overall relative intensity of the emotions, is also parameterised, but accessible only through the Ikaros XML protocol for the response module. This parameter setting, allows individual amplitude factors to be set on each emotion, thus governing their relative relationship in intensity between the emotions included.

Through such a parameterisation of the system, a transparency in what results are produced from cognitive modelling is achieved and an easily accessible interface is created for the response settings. In possible experiments involving the system, the parameter settings could thereby provide a well-defined basis for how the response is produced.

5 Conclusions and Discussion

This study presents a system for *1)* detecting touch, *2)* classifying different types of touch, *3)* relating touch and emotion *4)* relating emotions to a robot expression. A model of interaction through affective touch in robotics is introduced and the applicability of that model is examined through the construction of such a system. This is an investigation of whether a somatosensory system for a humanoid robot can be constructed from easily applicable components, in a solution that could be reproduced for different robots, and if the implementation of a corresponding response can enable a functional bi-directional interaction. The system for affective touch comprises the detection of touch on a robot head, the processing of a signal from detection, into a digital representation, of touch, and the classification of the type of affective touch applied, where an expression is produced as a representation of a related emotional state. It provides a bi-directional interaction in real-time, where touch interaction produces the communication of an emotional expression.

The system for affective touch is applicable to a humanoid robot that has an input of at least two hundred signal values from twelve different areas of touch over seven seconds. The quality of the identification of touch and the relevancy of its responses are significant to the applicability of the system. Machine learning has been used to enable the recognition of touch types "pat", "poke", "press", "slap", "stroke", "tap", "pick", "hold" and "rub", and a type, "none", for background noise. Data samples of touches on what was defined as primary and secondary areas of touch on the humanoid head were created and used for the training of two different machine learning models. Training on the total sample of touch types provides an accuracy above 85%, in the classification of touch, for the ten touch types, with similar values for an artificial neural network and a support vector machine model. The system relates touch to emotion, which in turn is related to robotic expressions. The certainty of the prediction of touch types is factored with values from an evaluation of related emotions to create a representation of emotion as response. Emotions are related to colour, by way of RGB value, where a representative value is produced from factoring the value assigned to the emotional response to the RGB value of the related colour. The rigidity of dividing affective touch into different touch types is loosened by allowing a combination of touch types to be represented by their values for certainty of prediction. A combination of different touches may provide information on applied touches that goes beyond singular categories, allowing for a complex modelling of affective touch and its responses. The response is divided into different stages, with possible different predictions of touch types and corresponding responses, in real-time interaction, as to provide a dynamical exchange. The system further allows for a consistent framework for the investigation of affective touch in robotics, by providing a parameterisation of its components. Such a parameterisation can further be used as reference for the setup of the system. The parameterisation includes possibilities for modifying the handling of the touches and emotions included, and whether to include previous emotions in the calculation of the current expression, as well as for the treatment of emotion with regard to its duration and intensity.

In the construction of a system for affective touch, many choices must be made regarding the definitions of touch, emotions and expressions and in relating their representations. Touch types are defined as patterns of touch and it could be that in this conceptualisation, the discrimination of touch types becomes too gross, where relevant attributes are excluded, as for example machine learning requires a division into characteristic patterns for learning to occur with a reasonable accuracy. It can be noted that in the training applied, the touches will tend to be differently executed, due to the human factor, thus adding variation to the data, but however within certain boundaries. The combination of different touch types in the system also makes possible a complex analysis of touch, beyond the limitations of the touch type definitions. The representation of emotion further requires gross estimates, as the literature overall does not provide detailed data on for example the scale of emotions, how different emotions may mix and merge, or interrelate over time. The strength of emotions is in this study factored with prediction certainties and normalised to fit the format of the colour expressions. This may exclude the scaling of emotions as they naturally occur, and in the system, a multiplicity of emotions are considered to merge into one emotional state and together produce an expression. The expressions produced are limited to the colour scale, and spread out over colour space, to provide a differentiation of expressions. Overall, the system could however be considered a principal assessment of the phenomena involved and may represent broad strokes of basic human functionality applicable to a humanoid robot.

The validity of the system could be further assessed through experiments involving human participants, providing their judgements on the quality of interaction. A system for affective touch, including possibilities for bi-directional interaction in real-time, could in this way be regarded a setup for experiments in humanoid and social robotics, involving touch. A future study could entail research participants applying touch, directly interacting with the robot and evaluating the identification and responses it provides. Further development could allow for such interaction to update the somatosensory system through learning during the course of interaction, including both supervised and, if possible, reinforcement or unsupervised learning, with direct responses from the research subject providing directing values for the learning process.

Location is of particular importance in affective touch. A setup alternative to the one of this study would have to be applied to, for example, distinguish between affective touch on the lips and the chin of the humanoid. To improve the design, a higher granularity of touch areas would be a first possible step, where this study was limited to twelve such areas. While the number of nerves in the human skin will not be approached in similar studies, an increase in points of detection would provide an important contribution to localisation. There is however a down-side in that materials for detecting touch tend to be expensive and inaccessible. In the identification of touch, it would further be of interest to enable the recognition of whether more than one hand is applied to the robot, allowing for additional important distinctions in touch types. This could be achieved by applying clustering algorithms, where a dependence on the spatial ability of the detection is again of importance, but where clustering may be carried out from the values of signal strength and a calculation of distance, based on the relationship between the sensory areas of the robot head. Pressure sensitivity is an additional factor, and an increased resolution in pressure could provide important characteristics to the classification of touch. A textile-based capacative material may be placed on the outside of a robot head as its contact surface, skin, and in direct contact with the touching hand. The application of pressure to such a textile could change its texture and with that its capacative detection. Video could further be used in conjunction with the detection of an electrical field, where this would correspond to the sense of sight and its effects on the perception of affective touch. The use of video would introduce a complexity of setup, but could contribute with important information to the recognition of touch. The importance of context to touch, including the history of interaction and dependence on personal relationships may be difficult to study, but is nevertheless of further great importance, if advances in the fields of humanoid and social interaction involving touch are to be made.

In the academic study of touch types, we can conclude that an improved foundation of definitions for touch interaction is needed. These definitions would benefit from including at least the following factors: *1)* part of the hand that is in contact, *2)* movement pattern, *3)* duration, and, *4)* pressure or force. The relationship between touch and emotion needs further study, as neurological studies of touch usually do not provide useful information on more direct links or mappings between these phenomena and studies that do make these connections do not provide details on those relationships.

The mechanism of measuring changes in capacitance, caused by touch, is not directly analogous to that of human touch, in which sensory neurons such as mechanical and thermic receptors provide the mechanism, but it provides a parallel function. For the purposes of this study in humanoid and social robotics, the detection and identification of touch is carried out in such a way that a parallel is established. The investigation of a system for affective touch has relevancy to the problem of perception, providing a model of the sense of touch, it enhances the humanoid features of a robot and furthers an understanding of the requirements for a functional social cognition. In humanoid and social robotics, robot behaviours cannot become exactly like those of humans, and the behaviours of current robots are overall far from directly correlated to human behaviour. In approaching an embodied interaction that includes touch, robots for the learning of children will become less of a novelty or temporary toy, as such development would lead to an increase in interest and deepen the meaning of exchanges in long-time interaction. Robots for the care of the elderly could through improved capabilities for tactile communication, with related responses and expressions, enjoy enhanced humanoid abilities, and acquire competencies for social interaction that are conducive to care.

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