Human Emotional Understanding for Empathetic Companion Robots

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Abstract Companion robots are becoming more common in home environments, as such a greater emphasis is required on analysis of human behaviour. An important aspect of human behaviour is emotion, both the ability to express and comprehend. While humans have developed excellent skills in inferring the emotional states of their counterparts via implicit cues such as facial expression and body language, this level of understanding is often neglected in Human Robot Interactions; furthermore, humans are able to empathetically respond to the emotions of others to create a more harmonious and person relationship. This paper is a preliminary proposal of a novel approach for facial emotional detection and appropriate empathetic responses, in conjunction with long term emotion mapping and prediction; the proposed system will be implemented on a social mobile robot, thus allowing a further level of behavioural comprehension to achieve a more human like encounter. The technique will be based on Fuzzy Cognitive Maps, using FACS Action Units as inputs, a high level facial descriptor layer and output of six emotions.

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1 Introduction

Can Human-Robot Interaction (HRI) be facilitated by incorporating an emotional consciousness model combined with an empathetic engine to achieve reactive empathetic services and long term comprehension of human emotional behaviours?

Two decades ago the robotics community started taking into account the dynamic aspects of humans, this created a new approach to HRI; from here onwards HRI started to change, and now robots are starting to take into account human behaviours. Human behaviour is complex and contains many aspects including but not limited to physical, psychological and emotional [1]. Recently there has been increasing bodies of work surrounding human behaviours from roboticists, with a specific interest in co-working tasks [2, 3]. This in turn has led to some robots starting to become behaviourally aware and able to learn from past experiences regarding human behaviour [4]. With an increased perception of behaviours, robots are able to tailor themselves towards the actions of those around, creating a more meaningful and person centred interaction [5]. Robots displaying emotion is a new concept and often limited to an animated face or similar, however this idea has led to more meaningful HRI interaction [6].

An important aspect of human-human interaction is empathy, the ability to understand and share the feelings of another. Empathy within geriatric care has shown to have a range of positive effects on clients including helping them settle into a new environment and aid in the recovery of bereavements [7]. Robots are starting to appear in nursing homes as aids for staff, as well as a companion for residents [8]. This highlights the need for robots to understand the emotional state of residents and treated them in an empathetic manner.

In Sect. 2 we review related work regarding emotional analysis and Fuzzy Cognitive Maps. Section 3 presents our proposed architecture to make use of Fuzzy Cognitive Maps, with Sect. 4 outlining our methodology for the experiment process to be explored based on real world scenarios. Finally we discuss the aims of our further work in Sect. 5.

2 Related Work

The Facial Action Coding System (FACS) [9], was published in 1977 and is the first approach to map facial features, and define them as Action Units (AU's) which relate to individual aspects of the face.

Facial recognition has become a prominent field of study, with the creation of freely available data sets such as Cohn-Kanade+ [10] and RU-FACS [11], researchers have been able to test techniques with centralised test sets. The data sets contain numerous images displaying facial emotions as defined by Ekman: Happiness, Sadness, Surprise, Fear, and Anger. Recognition from video and more so in real-time are challenging pattern recognition and computer vision problems, with to date no universally accepted approach.

Various pattern recognition approaches have been researched for facial emotion detection by classifying AU's including: Neurofuzzy Networks [12], Active Appearance Model [13], Support Vector Model [14] and combinations such as Hidden Markov Model and Support Vector Model [15].

Fuzzy Cognitive Maps (FCMs) were introduced in 1986 by Kosko [16] they are a soft computing methodology, an extension to cognitive maps. Salmeron proposed using a FCM approach for Artificial Emotional Forecasting in 2012 [17]. FCM is increasingly used in aspects related to human nature and behaviour; Akinci and Yesil, applied the proposal set out by Salmeron for emotional modelling using FCMs using multiple probes such as temperature and EEG as nodes for the FCM [18]. Fuzzy rule based logic has been used for facial emotional recognition by [19] attaining roughly 90 % accuracy; the approach attains higher accuracy than neural networks such as [20, 21]. FCMs however, lack a temporal aspect, furthermore, there is no accepted method for handling this. Acampora and Loia [22] implements a successful approach of dealing with the aforementioned issue, using a concept taken from formal languages, the timed automata. Other approaches that factor in time include Rule-Based Fuzzy Cognitive Maps [23], Dynamical Cognitive Networks [24] and Fuzzy Time Cognitive Maps [25].

Hereafter, a preliminary robotics architecture based on FCMs for human emotional understanding will be presented.

3 System Architecture

Our robotic system architecture can be seen in Fig. 1. Components in blue will be taken from state of the art. The key components we will develop are the Emotional Detector shown in green and the Trend Analyser in red. In order to achieve ours goals, the robot's reasoning module, will be tailored with three main factors: emotional consciousness, empathy and asynchronous, to create a deep and constant understanding of the emotion state of the user and react accordingly. The robot will work in an *asynchronous* manner by constantly analysing user's emotions creating an *emotional consciousness model*; which in turn enables *empathetic human-robot bi-directional communication*, wit the aim to create a comfortable and meaningful interaction for user. This model will be achieved by utilising FCMs.

3.1 Emotional Detector

We will use FACS as a recognition system for between eight and twelve different AUs that are seen as paramount in developing a facial emotional model. From these AU's, we will exploit FCM to define which of the six emotions is being displayed.

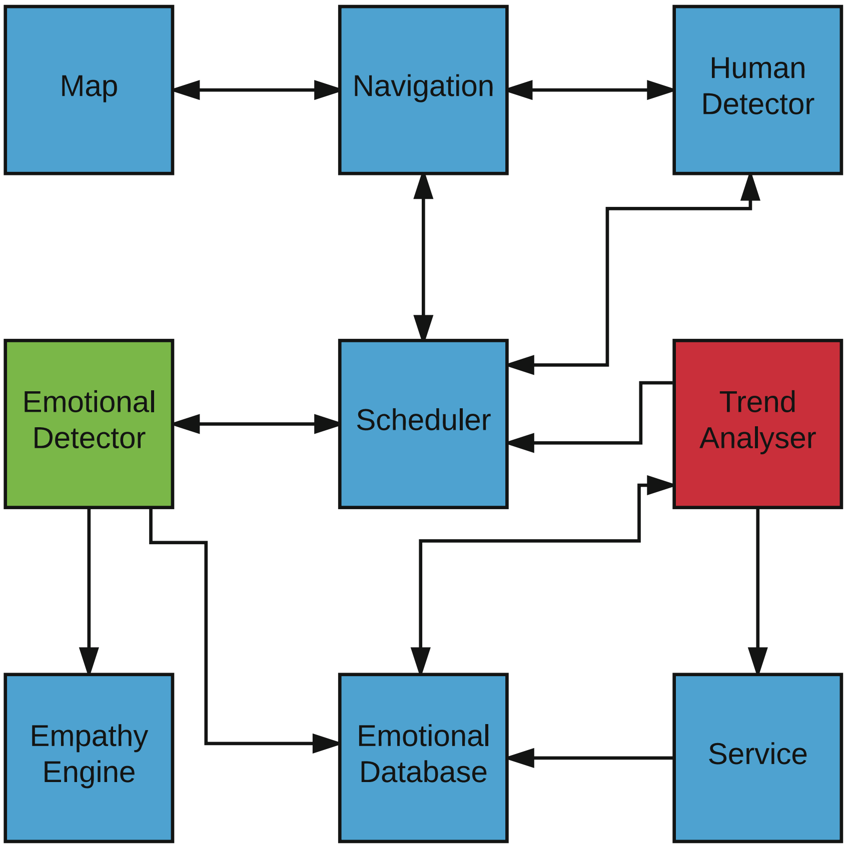

Fig. 1 Prototype data-flow diagram for proposed robotic system

A prototype our FCM model can be seen in Fig. 2, the model comprises of three layers: Input, Hidden and Output.

- *Input Layer*—Includes a node for each of the AU's used to define facial emotion
- *Hidden Layer*—Composite facial features e.g. smile, frown or eyebrow raised
- *Output Layer*—Each of the six emotions as defined by Ekman

Due to human emotions being sporadic and often only visibly displayed for a short period of time, it becomes of paramount importance to be able to handle these changes in a prompt fashion. Thus the concept of time is introduced to the system, unfortunately stand-alone FCM's are ill-equipped to handle temporal aspects. By using an extended FCM model we can add temporal concepts into the system; we propose using timed-automata-based fuzzy cognitive maps (TAFCM) [22]. "The system has two components: a timed automaton that describes the dynamic evolution of a system and an FCM that models the cognitive behaviour of (a) system during the first phase of its existence." With temporal concepts added to the FCM in Fig. 2, we should be able to achieve a more accurate representation of the emotion on display from the user over time. The detector will be trained using a percentage of the Cohn-Kanade dataset, using a Hebbian learning algorithm. The remainder of the dataset will be using for testing.

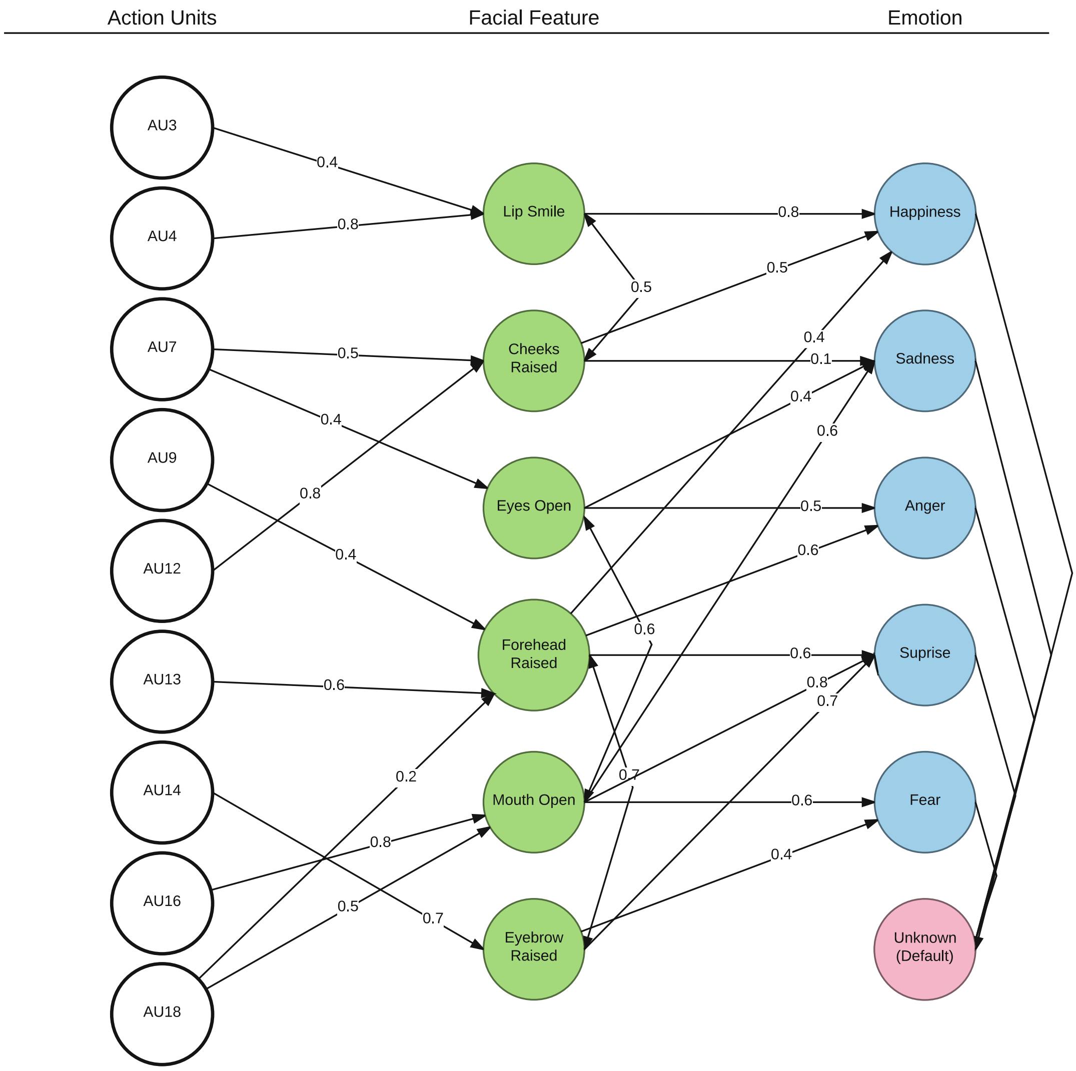

Fig. 2 One of the proposed Fuzzy Cognitive Map prototypes

3.2 *Trend Analyser*

The trend analyser is responsible for pattern matching emotions through extended periods of time. By incorporating this concept we hope to be able to pre-emptively predict times in which non-desirable emotional states may occur and pre-emptively react. By characterising emotional states as desirable or non-desirable we can apply services to attempt to alter undesirable states, such as anger to desirable such as happiness, any by recording what has positive outcomes can provide more meaniful services to the user. The trend analyser will work in tandem with the empathy engine and emotional detector in an attempt to create an artificial emotional awareness in respect to time and trends from the user. The development of the pattern recognition system will utilise FCM principles and constantly be updating with new information from the emotional database, scheduler and service provider. This will allow the system to monitor long term behavioural patterns, as well as highlight responses that may elicit a positive response from the user.

3.3 Empathy Engine

The empathy engine is the “heart” of the robot, its attempt to show empathy and emotional awareness in situations. The detected emotion will be used to elicit an appropriate empathetic response, in accordance with what is seen in humans; this principle can also be seen in [19] with appropriate responses based on fuzzy rules. We will use a screen with a changeable face, which shows an appropriate response based on the perceived emotional state of the user, i.e. if the user appears sad, the robot’s “face” may appear to show concern by lowering the eyebrows and narrowing the lips and mouth. Further to this a modulator can be added to the “voice” system, allowing the robot to speak slower with a soften tone, thus expressing concern and attempting to comfort the user. We believe a combination of emotional detection, trend analysing and an empathy engine, will allow a deeper level of connection between robot and human.

4 Experimental Methodology

4.1 Scenario

Simon is an elderly widower living in his own home. He receives 10 h of nursing support a week and has an on-call nurse 24/7; his family visit twice a week. Simons family have updated his house to include ambient intelligent technology and a robotic companion. Simon returns to his home and is angry about an argument he had with another resident. When Simon is angry he enjoys having classical music played. A conventional robot may attempt to greet Simon in a normal manner and ask him if he can be of assistance, this may frustrate Simon as he doesn’t want to be pestered.

4.2 System Core

The emotional detector, trend analyser and empathy engine are the core components in our approach. They are all required to perform their task to a high level to ensure all have the correct information for the system to work and respond effectively. We intend to use open source software for AU detection thus allowing more time to be focused on the interaction level rather than detection. The detected AUs intensities will be fed into our FCM system giving us one of six emotions as the current state of the user. The detected emotional state will be used by the empathy engine to provide an appropriate pre-determined response based on natural human responses i.e. if someone is upset we talk in a calm tone. Furthermore actions may also be suggested based on emotion, again using the upset example may receive a response of “shall we go into the kitchen and make a cup of tea?” in an attempt to distract the user’s mind from their mood. All of these used responses will be recorded by the trend analyser, recording the emotional state before, the time of day, what the system did and when the emotional state changed again. This will start to build a map of how actions affect the emotional state of the user, helping to define what action(s) should be tried in various scenarios. The system will map emotions over time, indicating if a particular undesirable emotion is detected at regular points in time. i.e. when somebody visits causing anger, this data can be seen by relevant parties and changes to routine or such could be made to accommodate.

Simon Example—Our proposed robot would detect Simon is in an Angry mood, as a result start playing his classical music. The robot would alter its demeanour i.e. showing a more caring face and using softer slower speech, whilst informing Simon it’s waiting if he needs anything. Whilst the interaction may have the same consequence as the conventional, Simon would be aware of the empathy shown by the robot in its action whether immediately or after he had calmed, helping build an emotional bond between the two.

5 Conclusion

Moving forward we will create multiple functional prototypes of the Emotional detector based on Fig. 2 and train the system to give suitable weights. A key step at this point is comparing it to systems that are readily available, thus allowing a in depth-review of our system prototype against current state of the art. Once a functional prototype has been developed an appropriate robotics platform will be selected. We will attempt to develop the system with an open-feedback loop for empathetical facial responses to the perceived emotional state of the user. The second part of the system regards learning likely changes in emotional states and using pre-emptive services, in an attempt to change to a more desirable emotional state; this works in tandem with the empathetical robotic system, showing emotions to the user and changing its behaviour in the hope the user will respond. We believe these key aspects of an emotionally aware, pre-emptive, empathetic robot, will be beneficial to HRI and help to build a more comfortable and meaningful interaction for users who may have disabilities or the elderly. By understand and displaying empathy, it adds an extra layer of communication that is a natural part of human-human interaction, but seemingly non-present in many of today’s robotic systems.

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