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"It's Amazing, We Are All Feeling It!" Emotional Climate as a Group-Level Emotional Expression in HRI

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Abstract

Emotions are a key element in all human interactions. It is well documented that individual- and group-level interactions have different emotional expressions and humans are by nature extremely competent in perceiving, adapting and reacting to them. However, when developing social robots, emotions are not so easy to cope with. In this paper we introduce the concept of *emotional climate applied to human-robot interaction (HRI)* to define a group-level emotional expression at a given time. By doing so, we move one step further in developing a new tool that deals with group emotions within HRI.

Introduction

Emotions are an inherent part of our lives. In fact, the processing of emotional information and the management of emotional dynamics intelligently proofs to be essential to navigate in the social world (Lopes et al., 2004). Therefore, when creating artificial agents and synthetic characters endowed with social behaviours, emotions must be considered throughout their process of creation.

Considering the creation of a social robot with empathic capabilities, as it occurs within the EU FP7 EMOTE project (www.emote-project.eu/), it becomes crucial to study how emotions are expressed and how they can be perceived by the robot to sustain engaging interactions. With the final purpose of integrating an empathic robot in group dynamics, understanding the group-level emotions will enable to create an emotionally intelligent robotic agent, capable of adapting its own behaviour to the group's emotions. To sustain such emotional perceptions, the field of computer vision (CV) for emotional recognition is ever growing with numerous applications related with the creation of social agents (Chen, Pau, and Wang, 2010).

Traditionally, emotions have been considered an individual phenomena, motivating the study for individual theories of emotional appraisal (*e.g.*, Smith and Ellsworth (1985)). Nevertheless, despite the fruitful and extensive research focused on individual theories of emotion, there is also a need to consider emotional expression in group interactions.

Moreover, when considering the social context of HRI, we can be facing group-level or individual-level interactions, which lead to distinct emotional expressions (Smith, Seger, and Mackie, 2007). Concepts such as *engagement* have been studied in individual and group HRI interactions, revealing that its expression changes across the group size (Leite et al., 2015). In the same study, results seem to show that engagement (or disengagement) is expressed differently according to the type of interactions, whereas ideally *"the robot should have different prediction models and, depending on the number of people around it, use the most appropriate"*.

Building upon the concept of *group-level emotional expression*, this paper aims to address an emerging concept in the field of HRI named *Emotional Climate* (EC), as a basis for understanding and studying the adaptive behaviour of a robot to the emotions of a group. The final goal is to have a robot interacting with groups of humans in a emotionally intelligent manner. It is expected that in the future this will allow the robot to be part of a group itself by being capable of understanding and reacting to its EC.

Emotional Climate and HRI

EC is a central element in social group interactions between humans and has been studied in many contexts, such as organizational environments (Tran, 1998), different social and cultural structures (De Rivera, 1992) and education within a classroom environment (Reyes et al., 2012). This paper proposes the adaptation of the latter EC construct within the field of HRI. In our approach, the EC can be defined according to the *valence state* of a group-level emotion at a given time. Following on this idea, EC can be divided into two valence states: *positive EC* and *negative EC*, defined according to the positive or negative qualities of the social and emotional interactions between and among the group elements at a given time.

While humans are highly competent at perceiving and adapting to group emotions, for social robots emotions are still a complex and hard construct to decode. With this in mind, we have made a first approach to map the concept of EC for HRI.

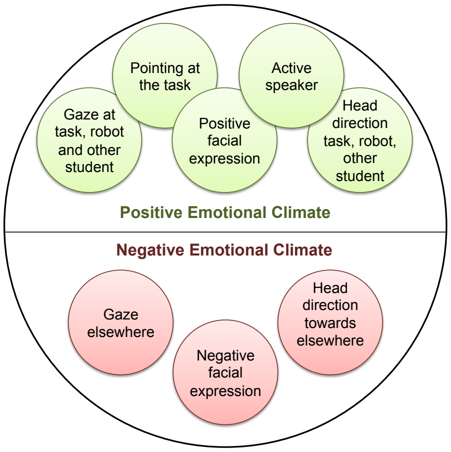

Figure 1: The emotional climate map for HRI showing how different emotional and behavioural characteristics may be used to assign distinct EC valences.

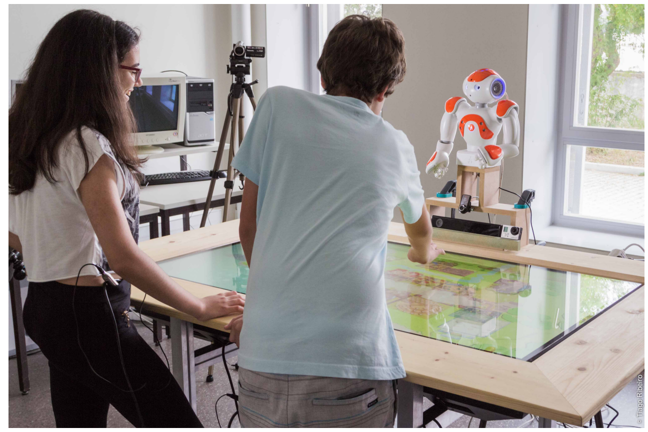

Figure 2: The set-up of our study, in which two students interact with a robotic tutor and play a collaborative game to raise environmental-awareness.

Mapping Emotional Climate

Tran (1998), proposed an *emotional map* to serve as an instrument to measure the EC in an organization. We took inspiration from the emotional map defined by Tran (1998) and adapted it for a specific HRI scenario, having into account the perceptions available to the robotic platform used in our studies. Figure 1 shows the proposed mapping of the EC within HRI, where we have divided it into positive and negative valences. Moreover, within this map different *emotions* and *behaviours* are assigned to each valence, thus translating the EC of a group at a given time. For example, a positive EC can be detected from different *emotions* (*e.g.*, a positive emotional expression) and *behaviours* (*e.g.*, participants are looking at the task and therefore are engaged in the learning process).

While in Tran's emotional map each bubble represents an emotion, in an HRI EC mapping, the inferred emotions are taken not only by *facial expressions* but also by *explicit behaviours*. The inclusion of both emotional expressions and behaviours in this mapping aims to meet the robot's real perceptual capabilities and at the same time grant it with enough social competences to manage and deal with group-level emotions.

Emotional Climate in EMOTE

With the goal of developing an empathic robotic tutor that is capable of perceiving and reacting to different valences of the EC detected from a group of students, we adapted the HRI emotional map depicted in Figure 1 in the context of a collaborative learning scenario within the scope of the EMOTE project. In addition, Figure 2 depicts the set-up of this scenario in which two students interact with an empathic robotic tutor in a school classroom environment and cooperatively play a serious game to raise environmental-awareness (Alves-Oliveira et al., 2014; Ribeiro et al., 2014; Sequeira, Melo, and Paiva, 2015). In this scenario, the students and the robot played the EnerCities[1] serious game, in which the goal is to build a sustainable city together raising awareness towards energetic, environment and economic implications of such. Within the EMOTE project, the original online single player game was adapted to a multiplayer version where participants interacted by using a multi-touch table or a tablet. This was done to stimulate collaborative learning between students themselves and between students and the robot. In addition, the robotic tutor was developed to be a peer companion in the serious game, but detaining more knowledge about the game itself (e.g., game rules) to be able to also act as a tutor and guide students through the game rules and dynamics and at the same time, having a similar hierarchical role in the game.

As emotions play an important role in education (Schutz and Pekrun, 2007), the perception of the EC of the students is essential to enable the empathic robot to adapt the pedagogical strategies to their difficulties and abilities, thus providing a high-quality support and assistance throughout their learning process.

Annotation Process

To create the HRI EC map, we performed video and audio analysis of 24 interaction sessions of approximately 20 min each in an earlier study made within the same collaborative learning scenario. We then used the mapping defined in Figure 1 to annotate the emotions and behaviours that students frequently exhibited when interacting with the robotic tutor and the corresponding EC valence of the students. The annotations were performed by 2 trained psychologists using the Elan tool (Brugman, Russel, and Nijmegen, 2004) and the Cohen's Kappa revealed $k = .76$, $sig. = 0.000$ of agreement between coders, translating a substantial level of agreement (Landis and Koch, 1977). From these annotations we were able to identify the time instants in which the annotator perceived a change in the EC valence and a set

[1]EnerCities: http://www.enercities.eu/

of emotional and behavioural characteristics of the students that seemed to influence the EC during the interactions.

Training of the EC System

We then developed a CV module based on the OKAO software package (www.omron.com/ecb/products/mobile/) that is able to translate the aforementioned emotional and behavioural characteristics of the students into *numerical visual features* that inform the activation level of each characteristic. Specifically, the CV module is able to detect the *gaze direction*, the *level of smile* and the level of several *emotional expressions*–namely *neutral*, *anger*, *disgust*, *fear*, *joy*, *sadness* and *surprise*. The module is able to detect the visual features of both students by analysing each video frame taken from a camera positioned in front of them and below the robotic tutor, as can be seen in Figure 2.

In order to identify the current EC in real-time, *i.e.*, while the students are interacting with the robotic tutor, we devised a Machine Learning (ML) module to learn a mapping from the visual features to an *EC valence label*. In that regard, we trained the ML classifiers by joining the annotated time intervals concerning the perceived EC with the visual features extracted during such intervals by the CV module.
[2]

We collected a total data-set of $68,410$ instances matching 20 visual attributes to one label, either *positive* or *negative*, gathered from the 24 interaction sessions. We then used the data from 19 of such sessions to train three different classifiers, namely a decision tree (J48), a multilayer perceptron (NN with backpropagation) and a support vector classifier (SMO) using the WEKA software package (Hall et al., 2009). Due to the discrepancy between positive and negative EC instances in our data, where only 3.2% of instances were labelled *negative*,
[3]

we used a resampling technique (SMOTE) to balance the amount of negative and positive instances in the training set. Afterwards, we used the other 5 sessions to test the learned models for each classifier, having achieved a 91.28% accuracy for J48, 62.06% for NN and 67.30% for the SMO classifier.

Having learned the classifiers, we designed a module to detect the EC and influence the behaviours of the robotic tutor during the interactions with students in the same collaborative learning scenario. We employed the same set-up used to train our ML system, *i.e.*, we positioned a camera facing the two students for the CV module to detect and filter the perceptual features online, sampling images at fixed intervals of $200ms$. Regarding the EC classification, we conceived a "totalitarian" voting scheme in which the current EC label was classified as *negative* only when *all* classifiers labelled the corresponding perceptual instance as negative, otherwise the EC was considered *positive*. This had to due with the fact that the classifiers were trained using a very small amount of negative instances compared to the positive ones as a consequence of the annotation process. Therefore, a negative EC is detected when at least one of the students exhibited emotions or behaviours that fit into a negative evaluation of the EC according to our mapping. In this case, even if the other student had a positive EC, the robot would adapt its behaviour in accordance. In practise, this means the robot will assist and support the learning process of students in a different manner, by, for *e.g.,* scaffolding.

After having determined its characterizing label, the current perception of the EC provided the possibility to influence the behaviour of the robotic tutor by changing the content and the way that certain utterances are performed. For example, if students were taking more time than the usual to decide what to do in the learning activity and a *negative valence of the EC* is detected, the robot could say: *"Sometimes it is not easy to understand what to do, but let me help you with that"*. On the other hand, if students were facing the same situation but a *positive valence of EC* was detected, the robot would say: *"Sometimes it is not easy to decide what to do, but taking time to think seems like a good option."*

Conclusions and Future Directions

In this paper we have proposed a novel way for social robots to deal with the emotions within group-level interactions. We introduced the notion of EC within the HRI context, highlighting the overall process of development and application, suggesting the potential benefits in having a robot capable of perceiving the EC of a group. We developed and adapted the EC concept in the context of the EMOTE project, specifically within an educational scenario where students interacted with an empathic robotic tutor. As a result, we developed a first attempt towards a robot capable of adapting its pedagogical strategy to the learning difficulties and abilities of students according to the EC that is detected at given time during the interaction. It is to note that this paper demonstrates the first steps of the application of the concept of EC within HRI. More specifically, this paper focused on three-party interaction with potentialities to explore the concept of EC for larger group interactions. For this to be possible, we believe that the perception system should be embedded with multi-modal data and multi-modal processing of informations from group interactions that are yet to be studied.

In the future, we aim to enhance the EC system by complementing it with physiological data, such as electrodermal activity and behavioural data from different systems (*e.g.*, provided by a Kinect system), thus going beyond the visual perceptual features. It is also our intention to have a prioritization system of the EC to target and select the most adequate behaviour of the robot for each situation in group-level interactions. We also want to highlight that the EC map presented in this paper can be adapted and applied to a diversity of HRI interactions, opening new ways to cope with humans emotions from the robot's development perspective.

[2]All features were processed with Kalman filters to smooth the corresponding signal and mitigate possible perceptual noise.

[3]This was due to the fact that the annotations showed that the overall interaction between students and the robotic tutor is characterized by more instances of positive EC rather than a negative EC. This happened because the HRI context was a collaborative learning activity in which students were engaged during the majority of the interaction time.

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