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Research paper

A cognitive architecture for modeling emotion dynamics: Intensity estimation from physiological signals

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Abstract

Current approaches to emotion recognition do not address the fact that emotions are dynamic processes. This work concerns itself with the development of a cognitive architecture for modeling the dynamics of emotions with specific focus on a gray-box model for dynamic emotion intensity estimation that can incorporate findings from appraisal models, specifically Scherer's Component Process Model. It is based on Dynamic Field Theory which allows the combination of theoretical knowledge with data-driven experimental approaches. A user study is conducted applying the proposed model to estimate intensity of negative emotions from physiological signals. Results show significant improvements of the proposed model to common methodology and baselines. The flexible cognitive architecture opens a wide field of experiments and directions to deepen the understanding of emotion processes as a whole.

Keywords: Emotion recognition; Appraisal; Component process model; Emotion intensity; Dynamic model; Cognitive architecture; Dynamic neural fields

1. Introduction

Current efforts in Human-Machine-Interaction (HMI) aim at finding ways to make interaction more natural. In this, knowledge of the user's emotional state is considered an important factor. Methods of automatic and reliable estimation of affective states from various modalities has therefore received much attention lately. In particular, emotion recognition from physiological signals is expedient, since it taps the pure, unaltered emotion in contrast to modalities like facial expressions which can be faked. It also does not require user's attention, which is important if one is assessing emotions in interaction studies or parallel to other tasks.

To date, most work on emotion recognition concerns itself with static prediction of emotion labels from a window of time series data using machine learning methods. But this approach neglects the consideration of emotion dynamics. This is not to be confused with features that capture dynamic properties of a signal within a certain time window that is being evaluated for its emotional content (see Jenke, Peer, & Buss, 2014; Valenza, Lanatà, & Scilingo, 2012). Static emotion recognition and machine learning approaches were important to understand basic differences in emotions and their general interaction with and effect on physiological signals. The ultimate goal of this field being sophisticated applications in real-world settings, however, makes an understanding of the whole emotion process necessary.

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Despite the shift of affective research towards capturing more subtle affective states, e.g. by using dimensional emotion models, the reliability of ground truth, duration and intensity of emotion are pertinent issues that have hardly been addressed (Gunes & Pantic, 2010). Although reliability of induction is often identified as a limiting factor, most studies are relying on operator labeled blocks of recordings to predict a targeted induced emotion label. In recent studies, this issue has sometimes been tackled by trying to identify phases of "strong feeling" post hoc, but intensity of emotion and particularly its evolvement over time is mostly left unregarded (Wen et al., 2014). This is probably also due to the fact that experiments that capture such dynamics are obviously harder to design.

To address the issues mentioned above, it might be fruitful to consider findings from modern emotion theory such as appraisal models. Mortillaro et al. has advocated to use appraisal in emotion recognition by suggesting to use appraisal as an additional layer in between expressive features and the predicted emotion label (Mortillaro, Meuleman, & Scherer, 2012). Yet, the most prominent finding is the fact that emotions are of dynamic nature and therefore, "require a dynamic computational architecture" (Scherer, 2009). We endorse this view and propose to emphasize consideration of the dynamic evolvement of the affective state in emotion modeling and recognition.

The remainder of this paper is organized as follows. Section 2 introduces representations of emotions, presents related work, and summarizes our contributions. Our general approach to combine appraisal with data-driven methods is presented in Section 3, where we also present the cognitive architecture that models emotion dynamics and discuss its main properties. As an application, Section 4 introduces the setup and design of a user study to estimate emotion intensity from physiological signals using the dynamic model. Results of the user study together with a discussion are given in Section 5. We conclude the paper with a summary and outlook of the proposed architecture in Section 6.

2. Related work

2.1. Representation of emotions

Emotion models are commonly divided into three major types: discrete or categorical models, dimensional models, and appraisal models. While the first two only represent the affective state of a person, i.e. a feeling not necessarily directed or attached to a particular object (Cowie, McKeown, & Douglas-Cowie, 2012), the latter aims at describing the emotion process as a whole.

Categorical or discrete emotion models are closest to what we use in our everyday lives when we use a single word to describe an affective state. Paul Ekman is probably the most popular representative of this model since Darwin. He derived the concept of six basic emotions *happiness*, *anger*, *disgust*, *sadness*, *anxiety*, and *surprise* from universally recognized facial expressions (Ekman & Friesen, 1986). In emotion recognition using classification methods, discrete emotion models account for the largest parts of studies carried out. From a computational point of view, these models are easy to implement, but it is difficult to model relations between the discrete states.

Dimensional models have been introduced, which overcome this limitation by providing distance between affective states, i.e. they allow for computationally interpretable relations between emotional states. In this, the VAD model suggested by Russell and Mehrabian is prevalent, which spans a three-dimensional emotion space of independent and bipolar dimensions *pleasure*-displeasure (later termed *valence*), degree of *arousal*, and *dominance*-submissiveness (Russell & Mehrabian, 1977). A 3D numerical vector denotes the location of an emotion within this space, so that discrete emotions have corresponding VAD coordinates. This model has gained attention in the field of emotion recognition lately, both in studies applying regression methods and studies that discretize dimensions into few areas, so that standard classification methods can be applied. Often, the third dimension is omitted (VA space). This circumplex model, which was discussed by Russell in 1980, uses the dimension *valence* and *arousal* and finds a circular arrangement of affect words which are described by angles (Russell, 1980). This representation of polar coordinates has yet found little attention in emotion recognition. Many other dimensional models exist, which have recently been integrated into a 12-point circumplex structure of core affect by Yik, Russell, and Steiger (2011).

Appraisal models take on a more general view: They define emotions as processes, derived from the notion that emotional episodes involve "changes in a number of organismic subsystems or components" (Moors, Ellsworth, Scherer, & Frijda, 2013). These models can explain underlying cognitive mechanisms of the emotional process in human beings by including appropriate components. All postulate an individual's subjective evaluation, i.e. appraisal, of the significance of an event (Scherer, 2009). They differ in the characteristic and number of components and appraisal dimensions considered. Leading appraisal theorists are Marsella, Gratch, and Petta (2010). The theory of the latter is particularly interesting for application to emotion recognition (Mortillaro et al., 2012).

Scherer proposes a recursive model of emotions, called the Component Process Model (CPM), in which emotions are emergent processes that constitute themselves from the appraisal of an event in interaction with different components (Scherer, 2009). Five functional components are involved (see Fig. 1): the cognitive component which includes the appraisal processes, the motivational component, the physiological efferent effects in the automatic nervous system (ANS), the motor expression component in the somatic nervous system (SNS), and the subjective feeling component. The cognitive component comprises a sequence of four stimulus evaluation checks (SECs): relevance, implications, coping, and normative significance.