Fuzzy gradual rules model for assessing emotions through physiological signals

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Abstract

Affective computing agenda is to enhance the quality of human computer interaction by making it more enjoyable by automatically recognizing and adapting to the user's affective states. More especially, it has a particular interest in the field of health such as providing emotional empathy for people living with autism. Therefore, there is need to develop methodologies for assessing user's emotional experiences. In this context, among a vast range of possible ways to access a user's emotional responses, physiological measures have a key advantage as they grant an access to non-conscious and non-reportable processes. However, to map physiological patterns from sensors to user emotional states remains a difficult task.

To begin with, physiological signals tend to vary from participant to participant and even within the same participant physiological signals vary from time to time. The current methods tend to rely on some forms of normalization using some baseline yet, the correlation between the baseline and the various emotions also vary from person to person and at different occasions for the same person. In this study, we propose a model based on gradual rules to characterize affective states of the form: *the more or less of A, the more or less of B.* Specifically, we consider the physiological signals variation with time during a particular affective state, such as: *Heart Rate increases with time during Joy more than 60% of the time or Heart Rate increases with time during Disgust less than 40% of the time.*

Secondly, emotions are conceptual quantities with indeterminate fuzzy boundaries. Besides, the physiological data from sensors is itself imperfect, such that it is difficult to express the results in crisp terms. Therefore, it is more natural to formulate a fuzzy set theory based model to represent these continuous transitions, uncertainties and imperfections. In this study, we consider a fuzzy approach to map physiological patterns to affective states. After we extract the support for each gradual item set, we define fuzzy rules to characterize the various emotions.

Keywords

Fuzzy sets, gradual rules, affective computing, physiological signals, machine learning

1. Introduction

Affective computing has become a major research interest in the Human Computer Interaction (HCI) community. Hence, there is a need to develop methodologies for assessing user's emotional experiences while interacting with these computer applications. In this context, physiology-based emotionally intelligent paradigms provide an opportunity to enhance human computer interactions by continuously evoking and adapting to the user experiences in

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real-time [1]. Research in this area has demonstrated the enormous prospects in developing systems equipped with the ability to assess user emotional states using various aggregation of physiological signal absolute value such as mean, minimum or maximum, power spectrum density ...and classical machine learning such as K-Nearest Neighbor, Linear Discriminant Analysis , Artificial Neural Networks, Decision Trees... [2, 3, 4, 5, 6]. Nevertheless, there is a need to develop more adequate models to represent the mapping of physiological patterns to users' affective states for real-life emotionally intelligent applications.

To begin with, physiological signals tend to vary from participant to participant and even within the same participant physiological signals vary from time to time. The current methods tend to rely on some forms of normalization using some baseline to tackle this variability. However, the correlation between the baseline and the various emotions also vary from person to person and at different occasions for the same person. Thus, these modelling approaches can not lead to a generalized mapping of affective states to physiological signals irrespective of the person and time. In this study, a way of extracting features that are independent of person and time of expression of the emotion, we consider a model based on gradual rules of the form: *the more or less of A, the more or less of B* [7, 8, 9, 10]. Specifically, we consider the physiological signals variation with time during a particular affective state, such as: *Heart Rate increases with time during Joy more than 60% of the time or Heart Rate increases with time during Disgust less than 40% of the time.*

Secondly,emotions are conceptual quantities with indeterminate fuzzy boundaries [11]. Therefore, it is necessary to express in fuzzy terms the mapping of affective markers from physiological data. In the context of continuously assessing emotions from physiological signals, change from one emotional state to the next is gradual rather than abrupt. Besides, the physiological data from sensors is itself imperfect, such that it is difficult to express the results in crisp terms [12]. Therefore, it is more natural to formulate a fuzzy set theory based model to represent these continuous transitions, uncertainties and imperfections. In a fuzzy set theory based model [13], changes from one rule to another is gradual with fuzzy values $[0, 1]$ instead of crisp values $\{0, 1\}$ in classical machine learning approaches. In this study, we consider contraction of fuzzy rules based model. After we extract the support for each gradual item set, we define fuzzy rules to characterize the various emotions.

2. Related works

2.1. Emotions and physiology

Studies in psychology have proved that certain psychological processes and states are accompanied by changes in physiological activity [14, 15, 16]. For example, Winton et al. [15]'s study showed that pleasant and unpleasant emotions could be differentiated through heart rate (HR). Pleasant reaction was found to be followed by heart rate increase while unpleasant slides were characterized by heart rate deceleration.

Subsequently, in affective computing, experimental studies have been conducted to propose the use of such inferences as a way to develop machines that can automatically recognize and respond to these emotions [2, 17, 18, 19, 4, 20, 5]. In particular, [2]'s study is well known in this domain. Their experimental study was aimed at discriminating eight emotions (*anger*, *hate*, *grief*, *platonic love*, *joy*, *love* and *no emotion*) through physiological measures recorded on a trained actor who was asked to express repeatedly these states over several days. Besides the results, one of the most striking revelation of their experiment was the complexity associated to the variability of physiological measures. Despite using the same participant for all the experiments, they observed a significant day-to-day variations. The physiological patterns associated to different emotions on the same day had the tendency to cluster together more tightly than physiological patterns associated to the same emotion on different days. Therefore, part of the aim of this work, is to present a possibility of determining viability of developing generic systems that could be applied independent of the user.

2.2. Methods of characterizing affective states

Modeling affective states through physiology has mainly been done through classification machine learning methods such as k-nearest neighbors algorithm, discriminant analysis, support vector machines, bayesian networks and decision trees [2, 18, 3, 4, 5].

These methods use features from the physiological signals during the period the emotion was expressed for each signal such as the average , maximum, minimum, standard deviation, power spectrum density . . . [6]. Absolute values of the signal tend to vary significantly from person to person and therefore they do some form of normalization or use of baseline to make the values comparable for emotion recognition. For example, given values $v1 < v2 < v3$, the same participant may have a value of $v1$ and $v2$ for $emotion1$ and $emotion2$ respectively on a particular day but same person may have value of $v2$ for $emotion1$ and $v3$ for $emotion2$ on a different day. The most widely used normalization is by min max so as to have values between 0 and 1 [0,1] [21].

The disadvantage with this approach is that it relies on only two values, minimum and maximum values. First, these two values may be outliers or suspectable to noise. They may not be a representative/typical of signal values. Secondly, its difficult to use this in real-time system as they have to be done post the emotional experience i.e, the normalization is in comparisons or an emotion vs other emotion values.

In this study, we consider a model based on gradual rules of the form: *the more or less of A, the more or less of B* [7, 8, 9]. The covariation of attributes such as *when* $Attribute1$ *increases,* $Attribute2$ *also increases.* It does not matter the absolute value of how much it increased as each person increase level tends to be different.

3. Our approach

3.1. Gradual patterns

Definition 3.1 (Dataset)**.** Let the data set $\mathcal{D}$ consist of n transactions: $\mathcal{X}_1, \cdots, \mathcal{X}_k \cdots, \mathcal{X}_n$ characterised by m attributes: $\mathcal{A}_1, \cdots, \mathcal{A}_p, \cdots, \mathcal{A}_m$.

	$\mathcal{A}_1$	$\mathcal{A}_2$	$\cdots$	$\mathcal{A}_p$	$\cdots$	$\mathcal{A}_q$	$\cdots$	$\mathcal{A}_m$
$\mathcal{X}_1$	$\mathcal{A}_1(x_1)$	$\mathcal{A}_2(x_1)$	$\cdots$	$\mathcal{A}_p(x_1)$	$\cdots$	$\mathcal{A}_q(x_1)$	$\cdots$	$\mathcal{A}_m(x_1)$
$\mathcal{X}_2$	$\mathcal{A}_1(x_2)$	$\mathcal{A}_2(x_2)$	$\cdots$	$\mathcal{A}_p(x_2)$	$\cdots$	$\mathcal{A}_q(x_2)$	$\cdots$	$\mathcal{A}_m(x_2)$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
$\mathcal{X}_i$	$\mathcal{A}_1(x_i)$	$\mathcal{A}_2(x_i)$	$\cdots$	$\mathcal{A}_p(x_i)$	$\cdots$	$\mathcal{A}_q(x_i)$	$\cdots$	$\mathcal{A}_m(x_i)$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
$\mathcal{X}_j$	$\mathcal{A}_1(x_j)$	$\mathcal{A}_2(x_j)$	$\cdots$	$\mathcal{A}_p(x_j)$	$\cdots$	$\mathcal{A}_q(x_j)$	$\cdots$	$\mathcal{A}_m(x_j)$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
$\mathcal{X}_n$	$\mathcal{A}_1(x_n)$	$\mathcal{A}_2(x_n)$	$\cdots$	$\mathcal{A}_p(x_n)$	$\cdots$	$\mathcal{A}_q(x_n)$	$\cdots$	$\mathcal{A}_m(x_n)$

Definition 3.2 (Gradual item)**.** A gradual item is a pair made of an attribute and a variation denoted by increase or decrease:
$\mathcal{A}_p \geq$ or $\mathcal{A}_p \leq$

Definition 3.3 (Gradual itemset)**.** A gradual itemset, $\mathcal{S}$ is a combination of two or more gradual items i.e a conjunction of two or more gradual items.
For example a gradual itemset $\mathcal{S}$ can be defined by the gradual items the more $\mathcal{A}_p$, the more $\mathcal{A}_q$ as follows:
$\mathcal{S} = \mathcal{A}_p \geq \mathcal{A}_q \geq$

Definition 3.4 (Length of gradual item-set)**.** The length of gradual item-set, is the number of gradual items in a gradual item-set.
For example a gradual itemset $\mathcal{S}$ can be defined below has a length of 3:
$\mathcal{S} = \mathcal{A}_p \geq \mathcal{A}_q \geq \mathcal{A}_r \geq$

Definition 3.5 (Support)**.** The total number of row pairs in the database that comply with a given item set divided by the maximum possible pairs in the database.

The maximum number of pairs is given by:
$\binom{n}{r} = \frac{n!}{r!(n-r)!} = \frac{n!}{2(n-2)!} = \frac{n(n-1)(n-2)!}{2(n-2)!} = \frac{n(n-1)}{2}$

If the number of pairs of rows that comply with a given gradual itemset, is z, then the support is given by:
$s = \frac{n(n-1)z}{2}$

3.2. Gradual patterns in physiological computing

In the current study, we consider extraction of attributes that represent the gradual rules. Instead of looking as individual features such as EDA and ECG separately;

STEP 1: Define a gradual item, *the more the time*, $\mathcal{T} \geq$.

STEP 2: For each attribute, define a gradual item, a pair made of an attribute and a variation denoted by increase or decrease: $\mathcal{A}_p \geq$.

STEP 3: For each attribute, define gradual itemset, $\mathcal{A}t_p$ as a conjunction of $\mathcal{T} \geq$ and $\mathcal{A}_p \geq$ i.e $\mathcal{A}t_p = \mathcal{T} \geq \bigwedge \mathcal{A}_p \geq$

STEP 4: Compute the support, $\mathcal{A}t_p$ and use it as the input for physiological characterization.

STEP 5: Construct fuzzy rules based on $\mathcal{A}t_p$.

4. Summary

In this study, we have proposed a generic model for characterizing affective states through physiology. First, we address the issue of invariability between person to person due to the nature of any bio-signal. In this regard, we proposed gradual rules based model of the form: *the more or less of A, the more or less of B.* Secondly, we have given direction to the most appropriate machine learning framework to handle the uncertainties and imperfections of online data captured by bio-sensors in real-time. In the characterization task, we considered contraction of fuzzy rules. As this work is a proposal, as a next step, we would like to test the model on real data and improve on its formulation.

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