A Decision Tool for Emotion Regulation Intervention

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Abstract

The recent popularity of wearable devices increased the public interest in utilizing technology to improve human emotional states. The primary goal of this project is to help individuals enhance their emotional states. For this purpose, users' physiological signals are collected in real-time with a smartwatch. Processing these signals, individuals can self-track emotions in various situations such as work, home, and party. Then the decision-making tool sends feedback to the user, considering her profile, preferences, and environment. The decision-making tool decides which approach works effectively for a specific type of emotion and an individual user. This process is repeated over time such that the individual's emotion is settled in the desired state.

Keywords: emotion recognition; emotion regulation; physiological signals; mobile sensing

1. Introduction

Emotion is a complex state of feeling in response to a particular stimulus that results in physiological and psychological changes. Traditionally, emotion detection and regulation have been skills that individuals can learn with the help of counseling psychologists. On the other hand, smart devices has been used to help users track their current emotional state and improve it. Recently, some researchers worked on how digital technologies can regulate people's emotional states [1]. (In this project, we develop a decision-making tool to mitigate individuals' emotional states using their physiological signals.)

According to a study by Feidakis et al. [2], human emotions have 66 types. They divided these types into two groups: ten basic emotions and 56 secondary emotions. It is challenging to discriminate such a huge amount of emotions because similar emotions have overlap in terms of measured physiological signals. Therefore, most studies focus on basic emotions that define easier, and they apply Russel's circumplex model of emotions which is shown in Figure1, which shows the distribution of basic emotions in two-dimensional space [3] to handle this issue.

There are several methods for emotion recognition but most of them are designed for laboratories and stable environments. In this article, we presented two methods of emotion assessment: self-report techniques[ ] and machine-assessment techniques. The former one uses questionnaires for emotions self-assessment and the later one uses sensors to measure human physiological signals [4]. This study is focused on automatic emotion recognition which is measuring physiological signals with smart-watches.

2. Data-Set

There is plenty of researches in emotion recognition using physical signals [4, 5, 6]. We assume the user's emotion elicitated from their physiological signals are given.

2.1. Data Simulation

The data-set simulated based on a recent study by Sharma et al. [4]. They have a data-set of 30 participants (15 males and 15 females, in an age range of 20–39 years) from different cultural backgrounds. We simulated a data-set with 60 participants(30 males and 30 females). We considered a more vast range of age groups(15-39 years) with more participants in each age group is shown in Table 1.

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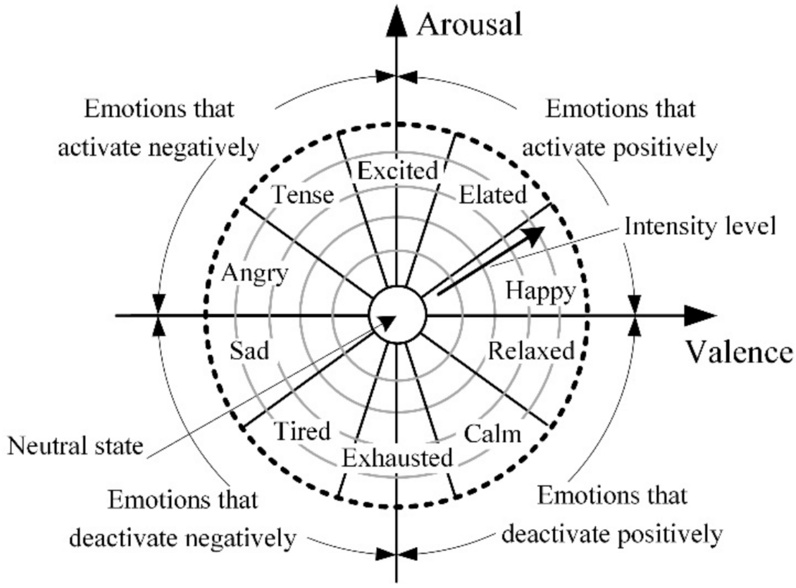

Figure 1: Russel's circumplex model of emotions [3]

Age groups	Number of Participants	Males	Females
15-19	11	5	6
20-24	17	7	10
25-29	15	9	6
30-34	9	4	5
35-39	8	5	3

Table 1: Demographics of participants in the simulated data-set

3. Problem Formulation

The system diagram shown in Figure 2 has two main subsystems. The first subsystem detects the emotion and the right block is the decision making block which finds the optimal feedback for the specific situation. The decision block decides on what action A_{t-1} has the optimal feedback for emotion regulation. This action changes the emotional state, X_t for the individual. As a result,the emotional state is a function of the emotional state in the previous step and the action A_{t-1}.

$$X_t = f(X_{t-1}, A_{t-1}) \tag{1}$$

In Figure 2, the emotional state, X, is measured based on the physiological signals, S. This signal and the individual profile are used to estimate the emotion probability $P(x)$. This profile includes different characteristics that change the emotion probability. For example, the normal heart rate can be different based on age and physical activity of the individual. The emotional state which has the maximum probability among m possible states, x_m,is the detected emotion, $\hat{X}$,

$$\hat{X}_t \simeq X_t = Argmax(p(x^m)) \tag{2}$$

We do not focus on the emotion detection block in this project and we assume the detected emotion is approximately equal to the current emotion.

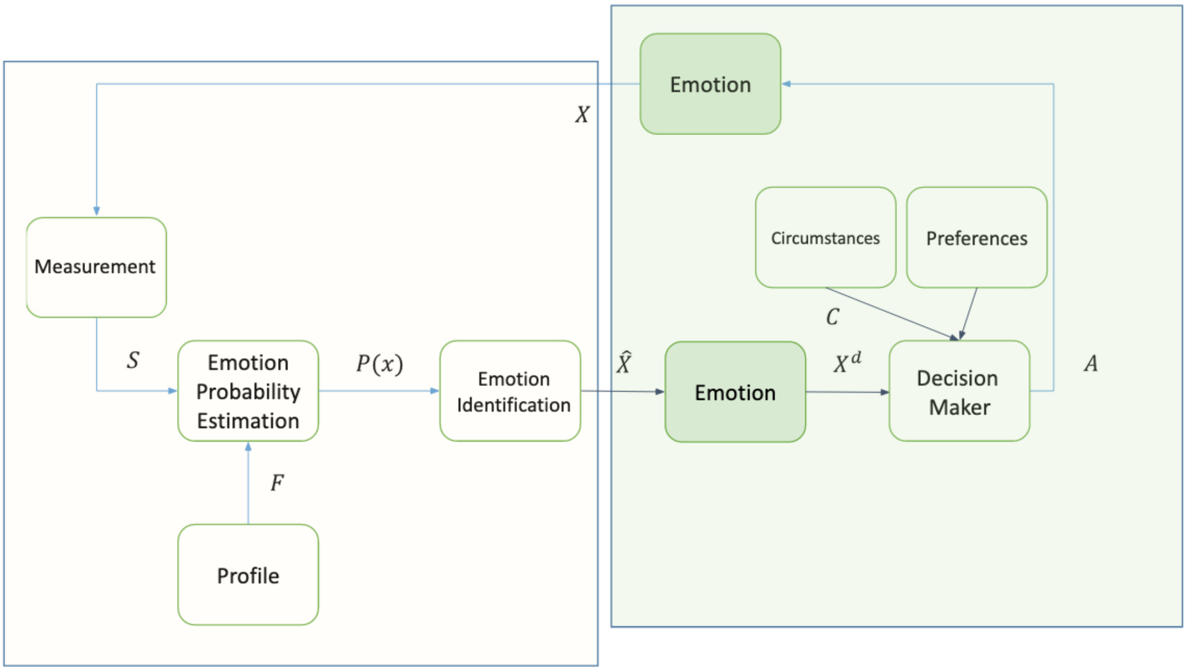

Figure 2: System Diagram

According to the Russel's circumplex model of emotions Figure 1, we are interested to switch from an emotion in the left side of the of the model exactly to the counter point in the right side of the model. For example, if the current emotion is sad, desired emotion will be Happy or if the current emotion is angry, desired emotion is R elaxed. The desired emotion, X^d, for a user is dependent on the the current emotion X. This is how we measure a distance between two emotions.

$$A_t = Argmin(X_{t+1} - X^d)^2 \equiv Argmax(r_i * e_j) \tag{3}$$

The loss function minimizes the differences between the desired emotion and predicted emotion in the next steps.

$$L = min \sum_t (X_{t+1} - X^d)^2 \tag{4}$$

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