Detecting depression using a multidimensional model of emotional states

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Abstract—Depression is a major problem in our society. It causes great pain and suffering for patients and their families. The purpose of this study is to detect persistent negative emotions for early detection of depression using physiological sensors. Therefore, we develop an automatic depression prevention tool using an algebraic model of emotional states. This algebraic model provides to represent emotions and provides powerful mathematical tools for the analysis and the processing of these emotions. It consists of representing and detecting negative emotions. Experiments show the efficiency of the proposed method in detecting negative emotions by giving high recognition rate.

Keywords-depression; algebraic representation ; negative emotions; physiological signal.

I. INTRODUCTION

Negative emotions (anxiety, fear, anger, and grief) may affect physical health and the quality of life. Indeed, people with depression experience severe and prolonged feelings of negative emotions like sadness, anger, disgust and fear. Depression is a common yet serious illness. It is a common problem that carries a high burden of suffering. In fact, the inability to diagnose clinical depression early, can have a serious impact on suffers, including the risk for suicidal ideation. Thus, Gotlib and Hammen [1] and Chynoweth et al. [2] demonstrate that most suicides are linked to depressive disorders and symptomatology. Depressed individuals experience prolonged periods of hopelessness, anger, guilt, desperation and a tendency to suicidal thoughts. Studies suggest that effective treatments for depression which may be aided by the detection of the problems in its early stages. In this context, and as part of GERHOME project [3], we aim to develop an automatic health care system that would assist mental health professionals by providing early warning-signs indicating whether a patient is likely to be depressed through their emotional states. The objective of GERHOME project is to create a research infrastructure that will enable experiments with technologies for improving the quality of life for the elderly. In fact, older adults generally want to be treated at home and with as little pain and discomfort as possible. Therefore our tool can be integrated in smart home (SH) in order to prevent depression and detect the mood disorders. For this, we use physiological signals to detect specific emotions and then to prevent depression. More physiological parameters can be measured directly by wearable sensors or can be derived from the analysis and correlation of different signals. For example, we can use a watch or a bracelet to capture the heart rate, an earring for Blood Volume Pulse and a shoe for the skin conductivity [4]. Therefore, our system permits to improve the quality and efficiency of health care at home by preventing depression. It is based on an algebraic model of emotional states [5] and it consists of representing and detecting of persistent negative emotional states.

The remainder of this paper is organized as follows. In Section 2, we defines depression and then we give an overview of related works on human emotion research. In Section 3, we describe our model to represent emotions. In Section 4, we describe our method of detection of negative emotion based on physiological signal and we conclude in Section 5.

II. DEPRESSION AND DESCRIPTIVE SCHEMES FOR EMOTIONS

In order to detect depression, our method is based on detecting negative emotions. In this section we defines depression and then we give an overview of related works on human emotion research.

A. Depression

Depression and anxiety disorders are highly prevalent worldwide. Statistics demonstrate that approximately 150 million people suffer from a major depressive disorder at any moment, and almost a million commit suicide each year [1] [6]. Depression is defined in medical dictionaries as a physiological and metaphorical lowering of emotional function. Someone with depression experiences extreme sadness or despair that lasts for at least two weeks or longer. Indeed one of the features of major depression is not that people have negative reactions to negative situations, it is that they cannot pull themselves out of those negative emotional moods [7]. Our goal is to detect persistent negative emotions in order to prevent depression.

B. *Descriptive Schemes for Emotions*

An emotion is the consequence of a feeling or the grasping of a situation and generates behavioral and physiological changes. Emotion is a complex concept. Darwin [8] said that emotional behavior originally served both as an aid to survival and as a method of communicating intentions. He thought emotions to be innate, universal and communicative qualities. Ekman [9], Izard [10], Plutchik [11], Tomkins [12] and MacLean [13] have developed the theory that there is a small set of basic emotions out of which all others are compounded. The most famous of these basic emotions are the Big Six, used in Paul Ekman's research on multi-cultural recognition of emotional expressions [14]. The Big Six emotions are happiness, sadness, fear, surprise, anger and disgust. According to research in psychology, two major approaches to affect modeling can be distinguished: dimensional and categorical approach. The dimensional approach models emotional properties in terms of emotion dimensions. It decomposes emotions over two orthogonal dimensions, namely arousal (from calm to excitement) and valence (from positive to negative) [15]. The second approach posits a finite set of basic emotions which are experienced universally across cultures (e.g., Plutchik [11], Tomkins [12], Ekman [9], etc) . In our study, we opted for Plutchik approach as the basis of our model and will thus describe it in details.

1) Plutchik model: Robert Plutchik proposed a three-dimensional "circumplex model" which describes the relationships between emotions. He proposed eight primary emotion dimensions arranged as four pairs of opposites [11]: (Joy-Sadness, Fear-Anger, Surprise-Anticipation, Disgust-Trust). The vertical dimension represents intensity or level of arousal, and the circle represents degrees of similarity among the emotions. He suggested that non-basic emotions are obtained through the addition of basic emotions (color analogy, Plutchik, 1962) [16]. In his model, for instance, remorse = sadness + disgust and contempt = disgust + anger. Plutchik defined rules for building complex emotions out of basic ones. In practice, combination of emotions follows the method "dyads and triads" [17]. He defined the primary dyads emotions as the mixtures of two adjacent basic emotions. Secondary dyad includes emotions that are one step apart on the "emotion wheel", for instance Fear + Sadness = Despair. A tertiary emotion is generated from a mix of emotions that are two steps apart on the wheel (Surprise + Anger = Outrage).

III. The Proposed Emotional Model

In this section, we present our approach of modeling emotional states. Indeed, the proposed model is different from traditional approaches like ontological representation. It is based on an algebraic representation using multidimensional vectors. We represent every emotion as a vector in a space of 8 dimensions where every axis represents a

basic emotion. This multidimensional model provides the representation of an infinity of emotions and provides also a powerful mathematical tools for the analysis and the processing of these emotions. The proposed model is similar to the RGB colors representation model which is based on three basic colors (Red, Green, Blue) to build all the others ones. For example, blue and yellow paints mix together to create a green pigment. In order to develop this analogy, it's necessary to define the basic emotions. For this, we will adopt the Plutchik definition of basic emotions which is a very intuitive and easy model including the idea that complex emotions are obtained by mixing primary ones. This last property is very important on our model because it allows us to define an infinity of combinations using the eight basics emotions defined by Plutchik.

A. *Definition*

The proposed model consists on the representation of emotions using multidimensional vectors. We represent every emotion as a vector in a space of 8 dimensions where each axis represents a basic emotion. First, we define our Base by (B) = (joy, sadness, trust, disgust, fear, anger, surprise, anticipation). So, every emotion (e) can be expressed as a finite sum (called linear combination) of the basic elements.

$$(e) = \sum_{i=1}^{8} \langle E, u_i \rangle u_i \tag{1}$$

thus, $(e) = \alpha_1 Joy + \alpha_2 sadness + \alpha_3 trust + .. + \alpha_7 Surprise + \alpha_8 anticipation$
where α_i are scalars and $u_i (i = 1..8)$ elements of the basis (B). Typically, the coordinates are represented as elements of a column vector E

$$E = \begin{pmatrix} \alpha_1 \\ \alpha_2 \\ . \\ . \\ \alpha_8 \end{pmatrix}_B$$

where $\alpha_i \in [0, 1]$ represents the intensity of the respective basic emotion. More the value of α_i get nearer to 1, more the emotion is felt.

In linear algebra, a basis is a set of vectors that, in a linear combination, can represent every vector in a given vector space or free module, and such that no element of the set can be represented as a linear combination of the others. We have demonstrate that (B) satisfies the spanning property and the linear independence property [5]. Thus, we proved that (B) = (joy, sadness, trust, disgust, fear, anger, surprise, anticipation) is a linearly independent spanning set.

B. Representation of basic emotions

A vector represents a basic emotion if it verifies the following property:

$$\forall i \in [1..8], \exists \alpha_i \ with \ \frac{\alpha_i}{\sum\limits_{i=1}^{8} \alpha_j} = 1 \qquad (2)$$

A basic emotion is described by a vector which contains a single non-zero coefficient. The following vectors represent some basic emotions:

$$E_{disgust} = \begin{pmatrix} 0 \\ 0 \\ 0 \\ \alpha_4 \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix}_B \qquad E_{sadness} = \begin{pmatrix} 0 \\ \alpha_2 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix}_B$$

where $\alpha_4, \alpha_6 \neq 0$

The proposed model takes into account the property of the intensity of the emotion. Indeed, each emotion can exist in varying degrees of intensity. The coefficients α_i determine the emotion intensity. According to the value of the coefficients α_i we can make the difference between annoyance, anger and rage or pleasure. So, rage is the basic emotion anger with high intensity. The multidimensional model provides the representation of an infinity of emotions and provides also a powerful mathematical tools for the analysis and the processing of these emotions. Indeed, we can apply the usual basic algebraic operations on vectors like the addition, the scalar multiplication, the projection and the distance in an Euclidean space. We are going to detail only the addition. For more details, you can see [5].

C. Vector addition

We have seen in the previous paragraphs that the mixture of pairs of basic emotions resulted of complex emotion. fear and sadness for example produce the complex emotion "despair". "envy" is a mixture of sadness and anger. In this part we define the combination between emotions as the sum of two emotion vectors. This addition is defined as the maximum value of coefficients (term by term). Let E_{1u} and E_{2u} be two emotional vectors expressed in the basis (B) respectively by $(\lambda_1, \lambda_2, .., \lambda_8)$ and $(\lambda_1', \lambda_2', .., \lambda_8')$. The addition of these two vectors is defined as:

$$E' = E_{1u} \bigoplus E_{2u} = \max(\lambda_i, \lambda_i') \ for \ 0 \leq i \leq 8 \qquad (3)$$

In this sense, the vector representing the emotion despair, which is mixture of fear and sadness, is defined as:

$$E_{despair} = E_{fear} \bigoplus E_{sadness}$$

Figure 1. Combination and opposites on the Plutchik's model

$$E_{despair} = \begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \\ \alpha_5 \\ 0 \\ 0 \\ 0 \end{pmatrix}_B \bigoplus \begin{pmatrix} 0 \\ \alpha_2 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix}_B = \begin{pmatrix} 0 \\ \alpha_2 \\ 0 \\ 0 \\ \alpha_5 \\ 0 \\ 0 \\ 0 \end{pmatrix}_B$$

where $\alpha_2 \neq 0 \ et \ \alpha_5 \neq 0$
In the same way, we can obtain the "vector form" of the other complex emotions states defined by Plutchik. These emotions combinations are shown on (Figure 1).

IV. METHOD OF DETECTION OF NEGATIVE EMOTIONS

In our study, we explore the use of physiological signals for detecting persistent negative affects. We elaborate an emotion recognition method from Physiological Data based on signal processing algorithm. Our method permits to recognize emotion composed of several aspects like simulated and masked emotions. The data used for this study comes from the data collected in the MIT Media Lab: Affective Computing Group [18]. MIT's data set comprised four physiological signals, obtained from the masseter muscle (EMG), blood volume pressure (BVP), skin conductance (GSR) and respiration rate (RESP) collected over a period of 20 days, concerning eight emotions: the neutral state, anger, hate, grief, platonic love, romantic love, joy and reverence.

Our approach is composed of two modules: training module and the recognition module. In the training module, feature vectors are extracted from emotion training patterns. In the recognition module, classification has been performed by using the K-Nearest Neighbor algorithm. The result is a 8 component vector representing the detected emotion. This
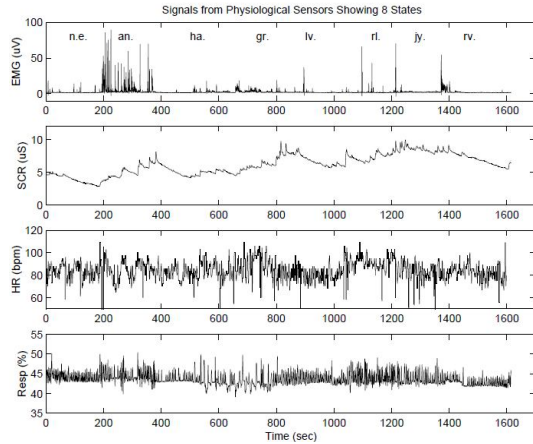
Figure 2.   An example of a session data collected from four sensors [18]
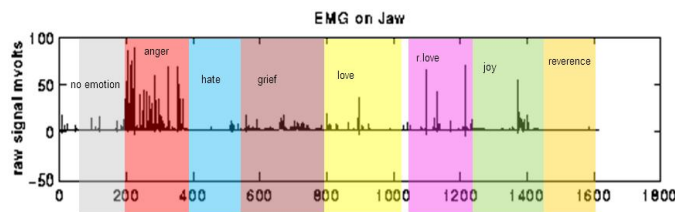

Figure 3.   Segmentation of the signal by emotion

vector is transformed to XML data thanks to the three layer model [19]. Let us here present the two modules of the proposed emotion recognition method.

A. Training module and features extraction

This session explains the proposed method to collect training data. Our newly developed method is based on feature extraction using signal processing techniques. The data consist of 25 minutes of recording time per day over a period of 20 days. Each day includes 4 signals showing 8 states in the order: the neutral state, anger, hate, grief, platonic love, romantic love, joy and reverence (Figure 2). Healey's original data was sampled at a rate of 20 samples per second, creating a digital version of the signal [18]. The signal processing for each sensor, include isolation of each emotion, smoothing, peak detection and features extraction (c.f. Figure 2). The global scheme of the features extraction is given by Figure 4. Firstly, we segmented the data, according to the emotions elicited at corresponding time frames (for example, although the recording time was 25 minutes, we only used the data from the time frame when the appropriate emotion (e.g., anger) happened). Let A designates the samples taken from any one of the eight emotions and any one of the four sensor (e.g., emotion anger, sensor: EMG). We process each appropriate emotion data separately to extract 30 representative vectors for this emotion. This is done by applying 3 major steps. First,
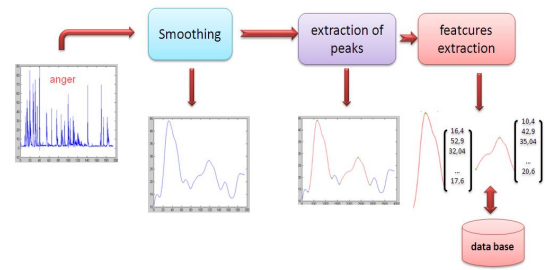

Figure 4.   The global scheme of the features extraction module

we smooth the signal to reduce its variance and facilitate the detection of its maxima and minima. That is why we apply Hanning window (smooth curve) [20]. Secondly, we compute the gradient of the signal and we apply the zero-crossings method to detect the peaks. Thirdly, we extract features for each emotion by computing typical statistical values related to peak, such as mean value, standard deviation, the amplitude and the width of peak. These data will be stored in a vector (the emotion feature vector) which corresponds to the appropriate emotion. Thus, we built an emotion training data base composed by 240 vectors representing the eight affective states.

B. Recognition module

The recognition module consists of two steps: (i) features extraction to have test data set and (ii) classification. Test data set was done by using similar steps to the training data, except that it does not have the emotion information. However, we used the K-Nearest Neighbor algorithm (KNN) [21] to classify an instance of a test data into an emotion classe. Infact, K-Nearest Neighbor (KNN) classification is a powerful classification method. The key idea behind KNN classification is that similar observations belong to similar classes. Thus, one simply has to look for the class designators of a certain number of the nearest neighbors and sum up their class numbers to assign a class number to the unknown.

In practice, given an instance of a test data x, KNN gives the k neighbors nearest to the unlabeled data from the training data based on the selected distance measure and labels the new instance by looking at its nearest neighbors. In our case, the Euclidean distance is used. The KNN algorithm finds the k closest training instances to the test instance. Now, let the k neighbors nearest to x be $N_k(x)$ and $c(z)$ be the class label of z. The cardinality of $N_k(x)$ is equal to k. Then the subset of nearest neighbors within class $(e) \in$ the neutral state, anger, hate, grief, platonic love, romantic love, joy and reverence is

$$N_k^e(x) = \{z \in N_k(x), c(z) = e\} \qquad (4)$$

We then normalize each $N_k^e(x)$ by k so as to represent probabilities of belonging to each emotion class as a value between 0 and 1. Let the lower case $n_k^e(x)$ represent the

normalized value. The classification result is defined as linear combination of the emotional class.

$$e^* = \sum < n_k^e(x), e > e \quad (5)$$

Thus,

$$e^* = n_k^{noemotion}(x) \ noemotion + n_k^{anger}(x) \ anger \\ + ... + n_k^{joy}(x) \ joy + n_k^{reverence}(x) \ reverence. \quad (6)$$

Thus, we build a probability model for each emotion class where $n_k^e(x)$ represents the probability of the respective emotion class. For example, if $k = 10$ and 8 of the nearest neighbors are from emotion class $anger$ and the other 2 are $grief$, then emotion class $anger$ has an intensity value of 0.8 ($n_{10}^{anger}(x) = 0,8$) and emotion class $grief$ has an intensity value of 0.2 ($n_{10}^{grief}(x)=0.2$). The classification result is defined as: $(e^*) = 0.8 anger + 0.2 grief$. Thus, our recognition method builds a probability model for each class and permits to recognize emotion composed of several aspects. Therefore, we get all the information on the emotion. This representation can be transformed, therefore, to the generic computational model of emotional states defined on Section 2 by applying the transformation matrix. Thus, we obtained eight emotional vector expressed in the basis (B). Then, we applied Plutchik's rules (c.f. Figure 2) to generate a data base of emotion for use at a later time. For example, grief is the basic emotion sadness with high intensity. Therefore, we can generate the emotion vector sadness. Either, we can generate the emotion vector "guilt" by combining joy and fear and the emotion vector "despair" by combining fear and sadness.

V. DETECTION OF DEPRESSION AND RESULTS

A. Detection of depression

We have already generated our data base of emotion, as explained before. It consisting of emotion vectors classified into 2 categories: negative and positive emotions. Negative emotions are, for example: grief, sadness, despair, hate, anger etc. Positive emotions are, for example: joy, romantic love, platonic love, reverence etc. Our method consists on detecting and classifying all the emotions felt throughout the day and give a global report. However, to analyze a given vector and determine the nearest emotion from the known ones we need a tool to calculate the similitude from the vector and the known emotions. For this, we propose to use the Euclidean distance (2-norm distance). Therefore, we have to compute for a given vector V1 the Euclidean distance between it and all the vectors of the data base. Then, we keep the vector of the data base minimizing the Euclidean distance. This vector represents the nearest emotion of V1 and the computed distance gives an idea of the precision of this interpretation. For example, we can found that the nearest emotion for the vector V1 is "despair" with a distance equals to zeros. We can affirm without doubts

that V1 represents the emotion "despair". More the distance from the nearest vector is important, less the interpretation is accurate. So, the proposed method, using the Euclidean distance, permits to analyze automatically a given vector and provides the best interpretation of this vector.

Algorithm 1 Detection of depression

1: int $negative\_day = 0$
2: **while** $negative\_day_¡14$ **do**
3:    **while** $True$ **do**
4:      $Wait\_for\_new\_day()$;
5:      $E_d=$ $Emotion\_Detection()$; //gives all the emotions felt throughout the day
6:      boolean $day\_is\_negative=positive\_or\_negative(E_d)$; //gives true if the new day is a negative day
7:      **if** $day\_is\_negative$ **then**
8:        $negative\_day + +$;
9:      **else**
10:        $negative\_day = 0$;
11:      **end if**
12:    **end while**
13: **end while**
14: $send\_alert()$;.

As previously stated, to detect depression we focus mainly on negative emotions. Therefore, we propose a method to classify all the emotions felt throughout the day and give a health check. For example, a day with more negative than positives emotions felt is considered as a negative day. In fact, according to [7] [22], a person who experiences negatives emotions for longer than a two-week period, may be diagnosed with major depressive disorder. Thus, the proposed algorithm calculates the number of successive negative days in order to prevent depression. If the number of successive negative days is greater than 14 (two weeks), our system conclude that the person could be suffering from depression and sends an alert message to the doctor (see algorithm 1).

B. Results

As shown in Figure 5.1, the analysis of the EMG signal using the proposed method, gives high accuracy percentage of detection of negative emotions. Indeed, we obtained for example 92% for anger and 62% for hate and 58% for grief. Figure 5.2 shows the results of accuracy obtained using the respiration (RESP) signal. Our method recognized anger with more than 73%, hate with 66.66% and grief with 50.58%. As know, it is hard to recognize emotions very accurately only with one modality. For this reason, we plan, for the future work, to conduct studies on multimodal recognition. Indeed, by applying two modalities, results could be improved up to 82%. Figure 6 gives an example of report generated after applying the algorithm of detecting depression along a period of 25 days. In the first scenario,
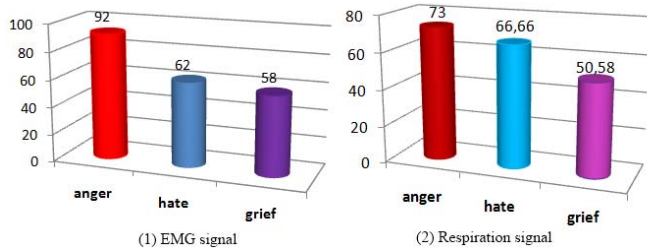
Figure 5. The classification rates of the proposed method using EMG and RESPIRATION signal
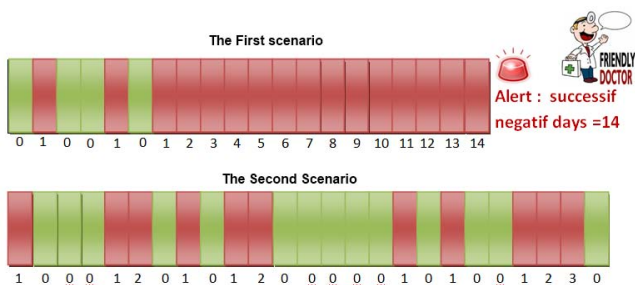

Figure 6. Depression detection

our algorithm calculate the number of successive negative days and conclude that the person could be suffering from depression and sends an alert message to the doctor. However, in the second scenario, our algorithm conclude that the person have a normal mood state.

VI. CONCLUSION AND FUTURE WORK

In this paper, we have presented a new approach for prevention and early detection of depression using physiological sensors. it consists of two main steps: the capture of physiological features and analysis of emotional information. The first step permits to detect emotions felt throughout the day. The second step consists on analyzing these emotional information to prevent depression. For emotion detection, we used signal processing algorithms to extract features and the the K-Nearest Neighbor algorithm to classify the emotion. Experiments show the efficiency of the proposed method in detecting negative emotion by giving high recognition rate. Finally, our system evaluate emotional information in order to detect depression and send an alert to the doctor. For the future work, we would extend our method to take into account others information such as voice communications, daily patterns of sleeping, eating, social interactions and online behaviors to improve prevention of depression.

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