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A Behaviour Patterns Extraction Method for Recognizing Generalized Anxiety Disorder

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Abstract—**Generalized anxiety disorder (GAD), as one of the most common chronic anxiety disorders, faces difficulties in clinical diagnosis. With the rapid development and wide application of smartphones in recent years, smartphones have a vivid application prospect in the field of mental disease monitoring and diagnosis. Based on WeChat applet platform on smartphones, an APP that integrates scale testing and inertial sensor data collection is developed to study the detection of subjects with GAD in task state. A behavior patterns extraction method is proposed using sliding windows to split behavior data, and processing data segments for clustering. Distribution information are extracted from the subjects' behavior patterns and are combined with the descriptive statistical features of the sample to identify GAD. The results show that this method has an accuracy of 66.44% for female subjects and 71.43% for male subjects in GAD recognition.**

Keywords-smartphone; behavior patterns; accelerometer; cluster; generalized anxiety disorder;

I. Introduction

Most mental disorders have become increasingly common across China in the past 30 years, among which the anxiety disorders have become the most prevalent one [1]. Epidemiological surveys indicate that one third of population is affected by a certain anxiety disorder during lifetime [2]. Most anxiety disorders are frequently co-occurred with major depression and are more pronounced in women [3]. Generalized anxiety disorder (GAD) is one of the most common chronic anxiety disorders with a range of physical and psychological symptoms. The lifetime prevalence of generalized anxiety disorder is 5.7% [4]. Moreover, on account of the key symptoms of the disease cannot be well recognized by the patient, while physical symptoms is frequently co-occurred, generalized anxiety disorder is difficult to be clinically diagnosed [4].

With the rapid development of mobile edge computing [5, 6] and wearable sensors [7, 8], the application scenarios of mobile devices have been widely extended. From patient care and monitoring to health and fitness APPs, smartphones have gradually transformed the field of medical [9]. Meanwhile, some research has already applied smartphones to mental health monitoring and treatment. For instance, a usage of mobile phone sensors to provide mental health behavioral markers for depressive symptom severity [10, 11], an emotion-aware cognitive system for multidimensional emotional data collection and approaches processing [12], a fine-grained sleep monitoring system on detecting the breath rate and sleep events by leveraging smartphones [13], a smartphone sensors based study on fine-grained behaviors by social anxious individuals during social interactions [14]. Therefore, smartphones' application on mental health is feasible and mature.

Patients with anxiety disorders often show some behavioral symptoms. They commonly present with some physical symptoms e.g. restlessness, excessive tension, worry, irritability etc. [15] These symptom characteristics are functional to distinguish GAD patients from health people from behavior perspective. Existing research on smartphone sensors or wearable devices has found that human behavior and mental health are closely related [11, 14, 16, 17]. A study [18] designed a task for patients with unipolar depression and bipolar depression, and revealed the difference between the healthy group and the depressed group under this task state. In another study on emotion-relevant activity, subjects were asked to perform a series of prescribed activity tasks. The results showed that under this experimental paradigm, body movement and posture will convey emotion-specific information.

We designed the experimental paradigm based on the above-mentioned related research. The experimental scenario requires participants to complete a self-evaluation. Participants are asked to complete mental health scales with smartphone, and their physical movements during this process will be recorded. In this task state, a clear separation of behavior events from a series of actions cannot be given, because in actual scenes, human body's small movements are often unpredictable and cannot be specifically classified as common actions, e.g. walking, lying down and falling. Therefore, this research tries using a sliding window to split the behavior sequence into fixed-length segmentation, and use unsupervised learning to cluster these fragments.

An online smartphone APP based on WeChat is developed to collect spontaneous behavior from subjects in self-evaluation task state. These data are processed using behavior patterns extraction method. Information will be extracted from the signal sequence according to the distribution of behavior patterns to distinguish GAD subjects

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from normal people.

In this paper, we propose a behavior patterns extraction method for generalized anxiety disorder recognition. This method is adopted to resolve the problem of classification of unknown behavior on task state and enhance recognizing generalized anxiety disorder.

II. METHOD

A. Data Collection App

WeChat is a free application offering instant messaging services which is widely used in China. An online psychological assessment system is developed based on WeChat applet as a web APP, which provides real-time assessment according to the subjects' answers. On the client, smartphone's sensor data is recorded when the subjects filled in the psychological scales, including gyroscope, accelerometer, and device motion by calling the API on smartphones with the sample rate of 5Hz.

B. Participants and procedure

Participants were recruited from Lanzhou University, Gansu, China, and signed informed consent forms online before the experiment. After signing the informed consent form, subjects were asked to sit in a seat and fill out psychological scales with the WeChat applet. The applet started to record the inertial sensor data when the start button is clicked and stop to record when user submit the result. One of the scales used in this experiment is Generalized Anxiety Disorder-7 (GAD-7).

Due to the lack of sensors in some mobile phones, or failure of some subjects to conduct in accordance with the procedures, 12 cases among were judged as invalid data. The participants after screening had a total of 84 generalized anxiety disorder subjects (49 female and 35 male, average 23.88 years old) and 84 normal controls (NC) (49 female and 35 male, average 24.83 years old). Among the participants selected for analysis, GAD-7 scores (GAD: average score of 13.79, NC: average score of 0.73) were the main criterion.

C. Data Analysis

1) Preprocessing: In this study, accelerometer sensor data is only used. Data preprocessing includes removing invalid data and performing dimension reduction. In the process of data collection, some subjects left their mobile phones on the table, while some walked around. Such data are not able to reflect real movement, so we marked them as invalid data.

The signal magnitude vector (SMV) conversion method is used to reduce the dimension of the original data and extracting magnitude information of the acceleration data [19]. The definition of SMV is shown in (1):

$$\mathrm{SMV}=\sqrt{x_i^2+y_i^2+z_i^2} \tag{1}$$

where x_i, y_i and z_i is the ith sample of the x-axis, y-axis and z-axis signal. The three-dimensional accelerometer data is reduced to a one-dimensional signal magnitude vector, and Euclidean distance is used to represent the change of movement without orientation information.

2) Feature Extraction: Before performing feature extraction, a sliding window is used to process accelerometer signal data. The sliding window method is widely used in behavior recognition, and has great benefits for identifying static activities e.g. standing and sitting and sporadic activities [20]. Each sample w_i are segmented using sliding windows, with each sliding window set to 5 seconds in size and 50% overlap. The window size and degree of overlap refer to the previous similar work summarized in [20]. Each window fragment j can be considered an undefined behavior. Sliding windows are represented as follows:

$$w_i=\{w_{i1},w_{i2},\cdots,w_{ij}\},\ \text{overlap}=0.5 \tag{2}$$

where w_{ij} represents the jth window of the ith data sample. Sliding window segmentation was performed for each sample to obtain an aggregate $\mathbf{W}$ of windows series. Each window would be extracted time and frequency domain

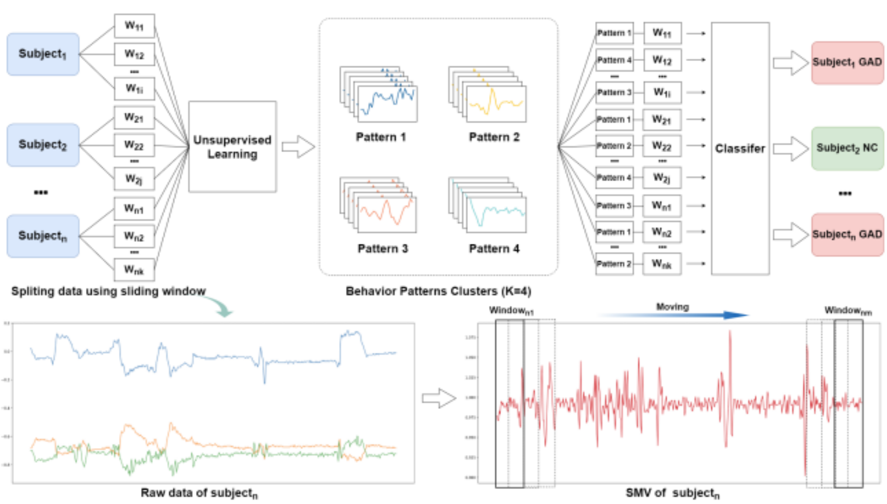


Figure 1. Framework of the behavior patterns cluster method

features for behavior patterns extraction. Feature extraction methods are as follows:

a) Time-domain Features: Time-domain features extraction of windows were mainly statistical features, including mean, standard deviation and root mean square (RMS). These features reveal the distribution state of signal magnitude vector within the range of this window.

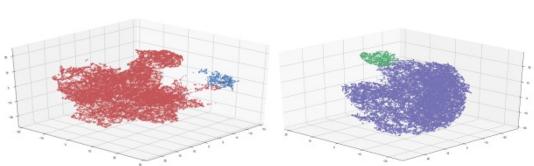
b) Frequency-domain Features: The first step in extracting features in frequency-domain is to perform a Short Time Fourier Transform (STFT) on the signal on each 5s window. The frequency-domain features extracted include spectral centroid and spectral energy.

The feature sets of these windows **W** would be used for subsequent unsupervised learning for behavior pattern extraction.

In addition, the descriptive statistical features of each subject are also extracted, including the median, interquartile, and interquartile range (IQR) of x-axis, y-axis and z-axis. The duration that participants spent in filling in scales is also considered as one feature.

3) Behavior Patterns Extraction: A research [17] revealed that there is a corresponding relationship between changes in behavior patterns and mental states. In some previous behavior recognition researches, movement classification or behavior recognition were based on independent behavior events given in advance. The behavior process of subjects can be commonly divided into specific events, and the start and end of each behavior can be clearly marked[14, 19, 21-23]. In our task state paradigm, movements of subjects cannot be divided into behavior fragments accurately. Therefore, we proposed a behavior patterns extraction method for GAD recognition on task state.

The framework of this proposed method is illustrated in Fig. 1. The upper part of the image is the process of behavior patterns extraction, and the lower part is the process of segmenting data using sliding windows. The segmentation and dimension reduction to the original data and the features extraction to windows have been mentioned above. $\mathbf{W}_{\mathbf{nm}}$ represents the m-th data window fragment of the n-th subject. The time series of each subject are not equal in length, so the number of windows obtained by segmentation is distinguished from each other. Each window can be regarded as a behavior, and K-Means clustering algorithm is used to cluster these windows (behaviors). The framework figure shows an example of K=4. The three-dimensional visualization display of the clustering results is shown in Fig. 2. Each color cluster represents the projection of a cluster of



(a) cluster 1 and cluster 3 (b) cluster 2 and cluster 4

Figure 2. Visualization of clustering results(K=4)

behavior pattern in three-dimensional space. Grid search method is adopted to determine the best K value that the classification model achieved the highest accuracy.

Eventually, the original accelerometer signal sequence of all samples was converted into a sequence of behavior patterns. We perform feature extraction

4) Classification: In this study, support vector machine (SVM) is chosen as classifier and recursive feature elimination (RFE) method is used for feature selection. Due to the difference of anxiety disorders in women and men [3] and possible Simpson's paradox [24], men and women are evaluated individually. At the same time, the classification effect was verified under different numbers of clusters.

III. RESULT AND DISCUSSION

In this paper, in order to exclude the influence of gender differences in behavior, male and female are modeled individually. The K value is traversed from 2 to 10, classifies under different genders. The result is shown in Figure 3. From the result it indicates the model got the best accuracy when K is 3 for female and 9 for male. The feature set corresponding to the best K value obtained above is used to

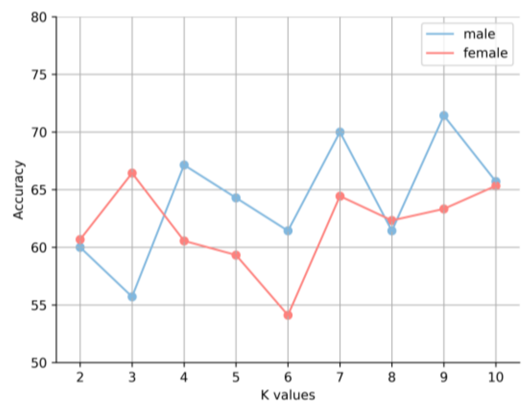


Figure 3. The best cross-validation accuracy of models under different K value

train the classification model.

TABLE I. CLASSIFICATION METRICS OF CROSS-VALIDATION

Gender	Metrics				
	K value	*Accuracy*	*Precision*	*Recall*	*F1*
Male	9	71.43%	68.25%	74.29%	70.08%
Female	3	66.44%	68.56%	67.00%	65.36%

Note: The results are the average of cross-validation.

It reveals that the model constructed by this method has a higher classification effect among male, the classification accuracy, precision, recall and f1 score are 71.43%, 68.25%, 74.29%, and 70.08%. It indicates the behavior pattern extraction method has a higher classification effect for male

GAD subjects.

Based on above results, a conclusion can be drawn that the behavior pattern extraction method is possible to identify generalized anxiety disorder. This shows that in self-evaluation task state, the behavior of GAD subjects is significantly different from that of normal control. Moreover, differences in behavior patterns exist between male and female.

In this study, sliding windows are used to divide sensor data into fixed-length segments and each segment represents a behavior pattern after processing and clustering in this study. We extract features from the sequence of behavior patterns and the original signal for classification. This method is more effective in identifying male subjects with GAD. In previous studies, researchers have proved that mental conditions can have a certain impact on human behavior [11, 14, 17]. The results in our study are present that people's behavior in task state is possibly related to anxiety symptoms. The behavioral differences between GAD subjects and normal people make this method efficient and effective in identifying GAD populations.

This method can identify GAD subjects during a short-term task of filling in scales. In the specific task scenario, human behaviors are unknown and difficult to simply define. This research extracts different behavior patterns of GAD subjects and normal people for anxiety disorder recognition. In future follow-up work, improvements will be carried in the amount of data and data sampling, including heightening the sampling frequency and the number of task scenarios. And a long-term tracking collection plan for the subjects' smartphone is also under consideration.

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