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A Novel Gait Analysis Method Based on The Pseudo-velocity Model for Depression Detection

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***Abstract*—As the occurrence of depression in society becomes increasingly more common, it is an urgent task to find more objective and effective tools for real-time depression assessment. Gait analysis offers a new low-cost and contactless method for depression diagnosis. Therefore, interest in gait-based depression detection using depth sensors, such as Kinect, has grown rapidly in recent years. In this paper, a pseudo-velocity model is built to analyze the abnormal gait related to the depression by combining the velocity and angular velocity of the joints. Subsequently, we extract some features in time and frequency domain from our model to establish the classification model for depression detection. Experimental results on depression gait data recordings from 43 scored-depressed and 52 non-depressed individuals show that the proposed method achieves a good classification accuracy of 92.35% and is superior to other existing methods. The outstanding classification performance suggests that the proposed method has potential clinical value in depression detection.**

***Index Terms*—Depression, Gait, Pseudo-velocity model, Time domain, Frequency domain.**

I. Introduction

Depression is one of the leading causes of various burden diseases. It has affected approximately 264 million people worldwide and is expected to increase in upcoming decades [1], [2]. In recent years, gait has received more and more attention in depression researches. Compared with other research methods, such as the use of audio, text, magnetic resonance imaging (MRI), and electroencephalogram (EEG) [3]–[6], gait acquisition does not require a high-resolution device and can provide a contactless method during the acquisition process. With the advent of low cost, non-intrusive depth sensors like Microsoft Kinect [7], we can trace human body dynamics accurately in a 3D manner without the assistance of additional markers or the requirement of specifically designed environment, further amplifying the advantages of gait analysis in the depression detection.

Because of these advantages, gait analysis has been increasingly applied in the detection of depression and has been shown to reliably distinguish depressed people from healthy individuals. Lemke et al. [8] reported a linear correlation between walking velocity and depression severity. In addition, a slouching posture was often reported as a prominent feature of patients with depression during gait movements [9], [10]. Another study on elderly depression suggested that shorter steps and slower gait were associated with depression [11]. Fang et al. [12] also found an association between gait abnormalities and depression, such as reduced walking velocity, smaller stride length, shoulder, and elbow range of motion.

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After reviewing related work on gait-based depression detection, we divide these studies into two main categories. First, researchers regarded human gait sequences as time sequences and recognized depression by the differences of gait parameters such as walking speed, stride length, and body sway [9]. Second, researchers performed feature extraction on gait data in the frequency domain. In [13], the authors used the frequency features obtained by the Fast Fourier Transforms (FFT) to establish a classification model for depression recognition. Reference [14] treated the trajectory of gait as a signal and proposed a new direction to detect the depression with frequency-domain features based on Hilbert-Huang transform.

However, some issues still exist in the current gait research for depression detection. On the one hand, although many studies have shown that lower walking style is the most significant abnormal gait characteristics in gait-based depression detection [8], [9], the current methods for the extraction of gait abnormality mainly focus on a certain dimensional coordinate of a few special joints and only concentrate on the frames with extremely abnormal gait, which leads to inadequate expression of gait abnormalities. On the other hand, gait analysis of patients with depression should not be limited to the gait parameters in the rectangular coordinate system, but it also considers other characteristics such as angular velocity in the spherical coordinate system.

To address these issues, we construct a pseudo-velocity model for the more comprehensive analysis of the gait skeletal data, by combining the velocity curve in the Cartesian coordinate system with the angular velocity curve in the spherical coordinate system. Then, some features in time and frequency domain are extracted from the pseudo-velocity model to establish the classification model for depression detection. Experimental results demonstrate that our method outperforms other methods considered for comparison with an accuracy of 92.35%.

The remaining part of this article is organized as follows: in section II, we introduce the gait data collection and describe the proposed method in detail. The experimental results are reported in section III. Finally, we conclude this paper in section IV.

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II. Materials and Methods

A. Data Acquisition

The research recruited 95 graduate students aged between 22 and 28. The Local Research Ethics Committee sanctioned the research and it also got the consent of the participants before the experiment. We divided the participants into two groups according to two classic scales: the Patient Health Questionnaire (PHQ-9, Chinese version) [15], Zung Self-rating Depression Scale (SDS, Chinese version) [16]. The non-depressed group contained 52 individuals (M: 28, F: 24), and the scored-depressed group contained 43 (M: 23, F: 20) participants. The basic information of the subjects is shown in Table I.

The experimental environment setting was similar to that of [12]. We required the participants to perform two round-trip walks in a daily normal state on the 10-meter footpath. Two Kinect V2 were installed in the middle of the ceiling at a distance of four meters, facing each other, with an angle of -27° relative toward the path. The cameras recorded the skeleton joint coordinate streams at a frame rate of 30 Hz. It should be noted that the two cameras were installed in the middle of the ceiling rather than recording data at the beginning edge, because the subjects' gait data might be the most stable and closest to the normal walking state at this time when they walked to the middle of the path.

B. Data Preprocessing

The skeleton streams used in the experiment are composed of 3D information from 25 joints of the entire body and the indexes of the joint points are shown in Fig. 1. In each recording, two Kinect devices recorded the skeleton gait data from both front and back views. Previous reports have confirmed that the effectiveness of using the skeletons from the front view is better than those from the back view [12]; thus, we use the segments in front view for our study. Although there is an angle of 27° between our camera and the horizontal plane, it does not affect the pseudo-velocity model we build later. In the end, we use a Gaussian filter to smooth the raw data in each dimension. It is implemented in MATLAB, with a sliding window length of 4.

C. Establishment of Pseudo-Velocity Model

Reviewing the current studies on gait-based depression detection, we find that gait speed is an important and significant feature among gait abnormalities [8], [11]. The authors of [12] also found that slower walking speed was correlated with other gait abnormalities. In our dataset, the difference in speed between non-depressed and scored-depressed also exists, as shown in Fig. 2. Furthermore, in previous studies, changes in speed over time have been proven to represent human movement. In [17], the authors suggested that the speed curve of joints calculated by the coordinate difference can represent the nature of walking. The time variable exhibited by the limb velocity was used to represent both emotional perception and expression in [18]. Therefore, we try to build a velocity model that can help us analyze the gait data of depressed patients.

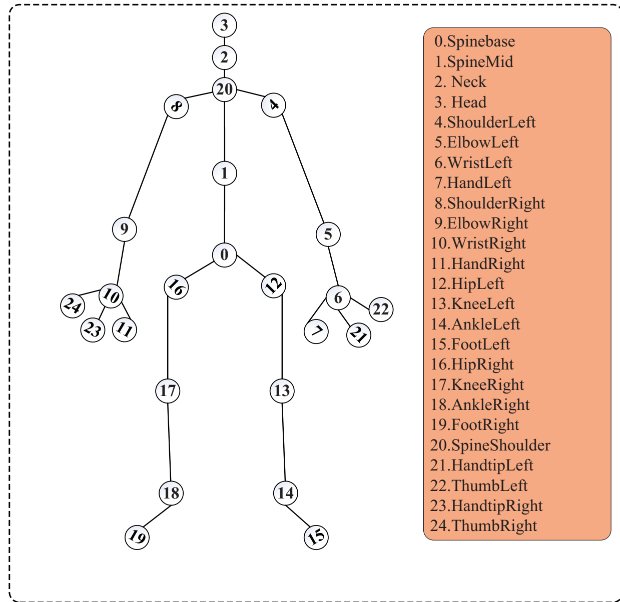


Fig. 1: The 25 markers on the human skeleton generated by Kinect V2.

TABLE I: Basic information of the scored-depressed and non-depressed groups.

	Scored-depressed	Non-depressed
Cases(n)	43	52
Sex, M:F	23:20	28:24
PHQ-9 (means $\pm$ S.D)	13.04$\pm$4.31	2.04$\pm$2.72
SDS (means $\pm$ S.D)	62.73$\pm$7.34	36.85$\pm$7.21

The original data is in the rectangular coordinate system. Each frame represents a different position of the joint point. We regard every coordinate of each joint in the 3D skeleton data as a time series and perform a frame difference to obtain the speed variation of each joint over time. In other words, we obtain the moving distance of each joint within 33ms, which is called the velocity curve. However, we find that the gait feature expressed by the velocity curve in the rectangular coordinate system is limited. Furthermore, some studies have regarded the angular velocity as a new action representation which could provide additional discriminative information [19], [20]. To better describe the pseudo-velocity model, we combine velocity in the rectangular space with the angular velocity information in the spherical coordinates. The conversion relationship between the rectangular coordinate system (x,y,z) and the spherical coordinate system (r, θ, φ) is shown in Eq.(1). Where r is the radial distance, θ represents the up and down pitch of the joint, as shown in Fig. 3a; φ represents the joint around the deflection, as shown in Fig. 3b.

$$\begin{cases} r = \sqrt{x^2 + y^2 + z^2} \\ \theta = \arccos \frac{z}{r} \\ \varphi = \arctan \frac{y}{x} \end{cases} \tag{1}$$

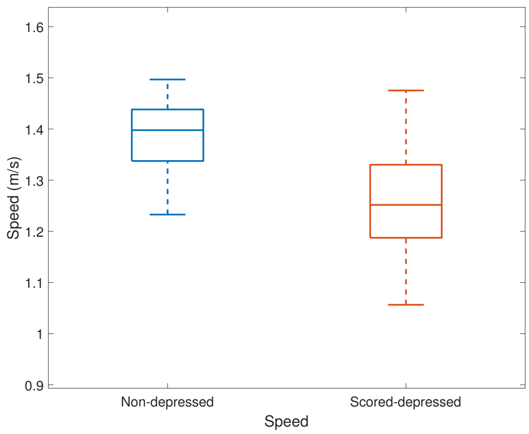


Fig. 2: The difference in speed between non-depressed and scored-depressed.

After mapping the data from Cartesian coordinates into spherical coordinates, we also calculate frame difference on the data in spherical coordinates to obtain the angular velocity curve. The pseudo-velocity model is constructed by combining the velocity curve and angular velocity curve. Let the parameter of the i^{th} joint in the f^{th} frame $Y_i^f = [x, y, z, r, \theta, \varphi]$, where $i \in [1, 25]$ and $f \in [1, F]$. F is the number of frames in the skeletal segment. The pseudo-velocity model is defined as:

$$\mathbf{V} = \begin{pmatrix} Y_1^2 - Y_1^1 & \dots & Y_{25}^2 - Y_{25}^1 \\ \vdots & \ddots & \vdots \\ Y_1^F - Y_1^{F-1} & \dots & Y_{25}^F - Y_{25}^{F-1} \end{pmatrix}, \quad Y \in \mathbb{R}^6 \tag{2}$$

D. Feature Extraction

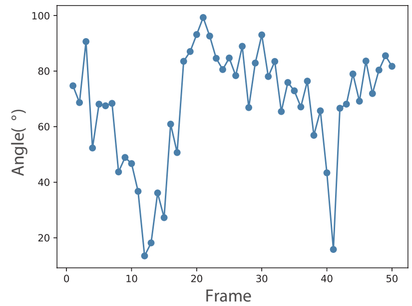
In this section, to comprehensively analyze the proposed pseudo-velocity model, we extract two types of features from our model, including time-domain features and frequency-domain features. The same feature extraction is performed on each dimension of the pseudo-velocity model.

1) Time-domain Features: In the experiments, we use a statistical approach to extract the time-domain features from the pseudo-velocity model [21], [22]. For each of the dimensions of feature $\mathbf{V} = [v_1, \dots, v_F]^{\mathrm{T}}$, the following statistical features are extracted.

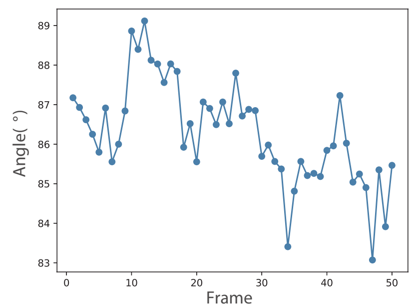
- Standard deviation of the signal measures the spread of the amplitude distribution, the standard division is computed as follows:

$$\sigma_{\mathbf{V}} = \sqrt{\frac{1}{F-1}\sum_{f=1}^{F}\left(v_f - \mu_{\mathbf{V}}\right)^2} \tag{3}$$

  where $\mu_{\mathbf{V}}$ is the mean of the signal.



(a)



(b)

Fig. 3: Head joint is represented in a spherical coordinate system. (a) Diagram of the head joint at θ. (b) Diagram of the head joint at φ.

- Skewness of the signal describes the asymmetry of the amplitude distribution, it is calculated as follow:

$$\xi_{\mathbf{V}} = \frac{\frac{1}{F}\sum_{f=1}^{F}\left(v_f - \mu_{\mathbf{V}}\right)^3}{\left\{\frac{1}{F}\sum_{f=1}^{F}\left(v_f - \mu_{\mathbf{V}}\right)^2\right\}^{3/2}} \tag{4}$$

- Kurtosis is computed to measure how the amplitude distribution decays slowly near the extremes, it is calculated as follow:

$$\gamma_{\mathbf{V}} = \frac{\frac{1}{F}\sum_{f=1}^{F}\left(v_f - \mu_{\mathbf{V}}\right)^4}{\left\{\frac{1}{F}\sum_{f=1}^{F}\left(v_f - \mu_{\mathbf{V}}\right)^2\right\}^{2}} \tag{5}$$

- Mean Trend describes the trend in the means over the signal. For a gait segment with definite length, we divide it into n equal windows with no overlap, in our approach, n=5. If the data cannot be evenly divided, we need to carry out zero filling. The mean for each part is calculated and subtracted from the mean of the following windows. The sum of the absolute values of these distances between adjacent window, called the mean trend, is calculated as follow:

$$MT = \sum_{i=2}^{n}\left(\left|\mu_i - \mu_{i-1}\right|\right) \tag{6}$$

where μ_i represents the average value of each window.

There may be some non-linear characteristics in our pseudo-velocity model. So in this paper, sample entropy is extracted as non-linear features to describe the characteristics of gait, which have been applied in the analysis of gait data [23].

- Sample entropy measures the complexity of time series data and has been widely and successfully applied in the analysis of biological signal sequences. The procedures of sample entropy are as follow:
  Given a time series data $\{x_i\}$ with $i \in [1, N]$, the original signal can be constructed into an m-dimensional vector as follow:

$$X(i) = [x_i, x_{i+1}, \cdots x_{i+m-1}], \quad i \in [1, N-m+1] \tag{7}$$

  where m is the embedding dimension and N is the length of time series.
  The distance between any two vectors $X(i)$ and $X(j)$ is defined as $d[X(i), X(j)]$, which is the maximum absolute difference between the corresponding elements in two sets of vectors, namely:

$$d[X(i), X(j)] = \max(x_{i+k} - x_{j+k}) \tag{8}$$

  where $k = 0, 1, 2, \ldots, m-1$.
  Given the value of the tolerance level r, for each i, the number of $d[X(i), X(j)] < r$ is calculated as N_i, and the ratio of N_i to the total distance $N-m-1$ is defined as:

$$B_i^m = \frac{N_i}{N-m-1} \tag{9}$$

  where $1 \leq j \leq N-m-1, j \neq i$, the average of B_i^m is calculated as follow:

$$B^m = \frac{1}{N-m} \sum_{i=1}^{N-m} B_i^m \tag{10}$$

  Based on the derivation of above, the Sample entropy is defined approximately as the following formula:

$$SampEn(m, r, N) = -\ln\left[B^{m+1}(r)/B^m(r)\right] \tag{11}$$

2) Frequency-domain Features: Some studies found that in the processing the gait data, the use of time-frequency features have better results [24]. Therefore, after obtaining the time-domain features, we try to extract the frequency-domain features from the pseudo-velocity model.

The power spectral density (PSD) is one of the most important frequency-domain features, it shows the strength of the energy as a function of frequency. In [25], the authors computed statistical features of the PSD of gait signals, which they then fed into the support vector machine (SVM) and naive bayes to classify the neurodegenerative diseases. In this study, the spectra are calculated via the periodogram method using a 128 point FFT and periodic Hamming windows. We perform the same PSD analysis on each parameter $[x, y, z, r, \theta, \varphi]$. For each axis a_n, the periodogram is defined as follow:

$$P(f) = \frac{1}{N}\left|\sum_{n=1}^{N} a_n e^{-j2\pi fn}\right|^2 \tag{12}$$

where N is the sampling length (measured in frames).

E. Feature Selection

Considering the high-dimensional feature is uninformative and redundant for classification, the dimension reduction is required before model training. We apply the Pearson correlation to select the 5 features with the largest absolute value of the correlation coefficient on each dimension, respectively. After feature selection, we obtain five features for each axis of each joint, which generates a $750(25 \times 6 \times 5)$-dimensional feature set in each segment.

III. Experimental Results

To verify the validity of the proposed method, a set of experiments are designed and conducted using the depression gait dataset of postgraduate students described in section II-A. We first analyze the classification results of different features. Then, we conduct a comparative analysis of the current methods.

After two types of features are obtained from the pseudo-velocity model, we normalize these features and feed them into SVM classifier with Linear kernel for depression detection. A linear kernel SVM has good performance in the case of small number of training samples and large number of features and can also reduce the risk of overfitting the data [26]. In this study, SVM is implemented using LIBSVM toolbox [27] with default parameters, which has been successfully applied to gait analysis [12]. We adopt a 'leave-persons-out' protocol, keeping all segments of a person as the test set and the other segments as the training set. In the prediction step, the accuracy, sensitivity, specificity, F1-score, and the area under the ROC curve (AUC) are used to evaluate the performances of the proposed method.

A. Classification Results With Different Features

To determine which set of features derived from the pseudo-velocity model can best represent the gait signal, several experiments are conducted with different combinations of two types of features. The obtained results are presented in Table II.

In the case of using only time-domain features, the classification accuracy is 71.18%. When frequency-domain features are used, we achieve an accuracy of 91.61%, with a sensitivity of 89.13% and specificity of 94.12%. By contrast, the accuracy of using the time-domain and frequency-domain features can reach 92.35%. Furthermore, the sensitivity and F1-score of the fused feature are also improved by 5.1% and 2.33% respectively. This finding indicates that the fused feature in the time and frequency domain is a more discriminative feature for classification. Therefore, the fusion of the two types of features is selected for subsequent experiments

TABLE II: Comparison of the classification results with different combinations of time-domain features(TF) and frequency-domain features(FF) in terms of four evaluation criteria (accuracy, sensitivity, specificity, and F1-score).

	Accuracy	Sensitivity	Specificity	F1
TF	0.7118	0.7596	0.6364	0.7633
FF	0.9161	0.8913	**0.9412**	0.9145
TF+FF	**0.9235**	**0.9423**	0.8939	**0.9378**

TABLE III: Comparison of our method with other methods in terms of various evaluation criteria (accuracy, sensitivity, specificity, F1-score and AUC).The best results in this table are labeled in bold.

	Accuracy	Sensitivity	Specificity	F1	AUC
Yuan et al. [14]	0.8304	0.8347	0.8252	0.8417	0.9182
Fang et al. [12]	0.9158	0.8605	**0.9615**	0.9024	0.8994
Our method	**0.9235**	**0.9423**	0.8939	**0.9378**	**0.9783**

B. Comparison With Different Methods

To investigate the performance advantages of our approach, we also compare our approach with several similar gait research methods. Leveraging the Hilbert-Huang transform to extract frequency features, a method for classification of depression detection from gait information was presented in [14]. The authors of [12] applied abnormal gait features in the time domain to identify depression. The results of the proposed method and the other methods are shown in Table III.

As shown in Table III, the proposed method achieves the highest accuracy compared with other existing methods. At the same time, we find that F-score and AUC have a significant improvement, indicating that our method has a stronger generalization ability. To more intuitively illustrate the validity of the proposed method, we plot the results from different studies in a radar chart, as shown in Fig. 4. According to the data in the figure, our method performs well and the indicators in all aspects are more balanced. Thus, with the time-domain and frequency-domain features extracted from the pseudo-velocity model, our method is proven to be very effective, which can reduce model complexity and enhance the classification performance.

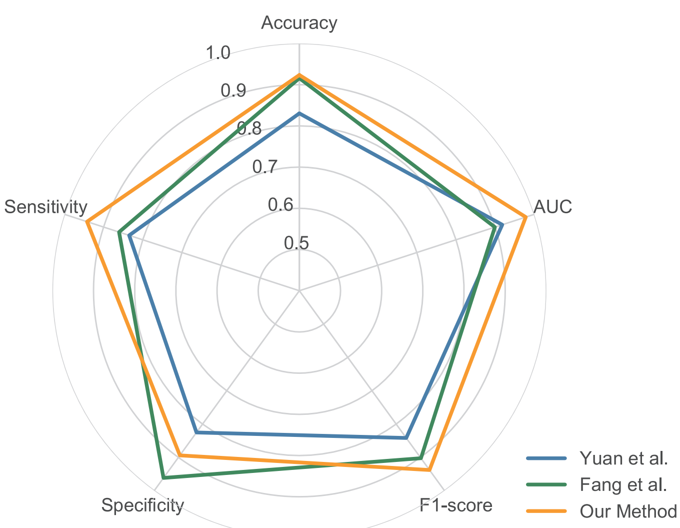


Fig. 4: Comparison of classification performance between our method and other methods. The best results in this table are labeled in bold.

IV. Conclusion

Gait analysis offers a new low-cost and contactless method for depression detection. By analyzing the gait behavior of patients with depression, we find that velocity plays an important role in the classification of depression. Therefore, in this paper, we establish a pseudo-velocity model to analyze gait abnormalities in individuals with depression; the subsequently extracted features in time and frequency domain can well support depression detection. Experimental results show that the pseudo-velocity model and the features extracted from it can effectively identify depression. The proposed method provides a non-intrusive, real-time, and automatic depression detection.

However, in the current study, we only consider the gait skeleton data from the front view. To obtain gait information more comprehensively and precisely, we can reasonably arrange the positions of the Kinect devices to obtain gait data from multiple angles in the future. Another issue is that we only make a binary classification of depression patients and do not consider the degree of depression. Patients with different degrees of depression may differ in analysis methods and feature extraction, so more research on the relationship between the degree of depression and its features need to be conducted in the future to better support depression analysis.

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