

A New Skeletal Representation Based on Gait for Depression Detection

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Abstract—As the challenge of depression problems increases today, it is important to effectively and timely detect for patients' treatments and depression prevention. Current methods of automated depression diagnosis depend almost entirely on audio, video, and Electroencephalogram (EEG) etc. In this paper, we propose a novel method to detect depression using gait data that is collected by Kinect camera. Its key components include a camera rectification method and a rigid-body representation of the human body. The camera rectification method achieves the purpose of improving data processing accuracy by changing the camera angle. The rigid-body representation can not only improve the robustness of detecting depression patients with noisy input, but also can reduce the classification time. We evaluate our method on the depression gait dataset in postgraduate students. The proposed method has an outstanding performance in classic machine learning algorithms, and the best accuracy can achieve 88.89%. Our solution provides a new method for automatic depression detection (ADD) that has exciting implications in clinical theory and practice, and has the advantages of high accuracy, inexpensive, low time cost, and no-contact.

Index Terms—Depression, Gait, Kinect, Rigid-body representation

I. INTRODUCTION

Depression is a common mental disorder in modern society. According to World Health Organization (WHO), more than 264 million people in all ages suffer from depression. Depression can cause the affected people to function poorly and is a leading cause of committing suicides [1], [2]. Patients with depression must be identified and treated promptly to avoid unnecessary loss. Nevertheless, the traditional mental disorder diagnosis in the clinic is based on self-report assessment tools, it is prone to subjective biases [3]. With the advancement of computer science and artificial intelligence, it proposes a novel approach for automatic depression detection (ADD).

At the moment, the application of artificial intelligence in ADD mainly focuses on video, audio [4], [5], text [6], and physiological signals [7]. However, the above detection methods have the disadvantage of requiring the participants actively cooperate. For example, Electroencephalogram (EEG) signal collection requires participants to wear a special helmet. Therefore, some researchers focused on other methods to detecting depression.

Some studies conclude that there is a significant difference between depressed people and healthy people in gait [8], [9]. In comparison with healthy people, the stride length of depression patients is shorter and the gait speed is slower. With the above basic research, many researchers turn their attention to how to identify depression with gait using computer technology.

As the research on depression gait is still in its infancy, there is great potential in many aspects. The clinical experience shows that the gait of depression patients has its distinct kinematic characteristics. Nevertheless, the current research directly uses raw gait data, ignoring the characteristics of human movement and the relationship between different joints. It leads to data redundancy, which affects the detection results and computation time. However, specific analysis model may be needed to capture the kinematic characteristics of depression patients.

In response to the above problems, we put forward a new solution for ADD, as illustrated in Figure 1. First, in order to collect the participants data and achieve the goal of no-contact, we installed the Kinect camera on the ceiling. Since the device is not directly facing the human body, we propose a new method of camera angle correction to help data processing. Second, according to the clinical behavioral characteristics and joint energy, which based on the kinetic and potential energy during gait movement, we propose a novel rigid-body representation. In this model, we select a gait neutral pose (GNP) and define the potential energy. We calculate the kinetic energy based on the speed of the joint. Depending on the amount of joint energy, we use torso that consists of the spine, hips, and neck as a rigid body to reconstruct the joints. Finally, traditional machine learning algorithms such as Support Vector Machine (SVM) [10] are used to classify the data.

We conduct extensive experiments using a real dataset collected by postgraduate students. The results showed that our proposed method can achieve 88.89% accuracy. Our method has the advantages of high accuracy, inexpensive, low time cost, and no-contact comparing with other detection methods such as audio, video, and EEG, and providing innovative ideas for ADD.

Our major contributions are summarized as follows:

- This study advances the state-of-the-art in ADD by de-

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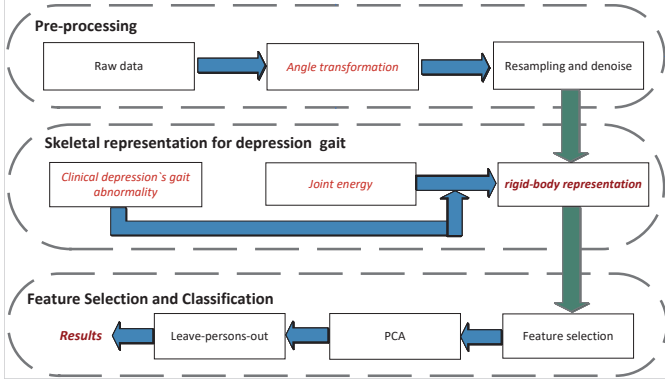


Fig. 1: The pipeline of our proposed gait-based ADD method.

veloping a new method of detecting depression with gait.

- According to the characteristics of our experimental data, we propose a method of camera angle transformation. This method can help us better fit the actual movement of the participants.
- We propose a novel skeletal representation model for depression detection using gait based on the concept of the rigid-body. This rigid-body representation method reduces the original data by more than half and improves the classification speed and accuracy.

II. RELATED WORK

A. Automatic depression detection

At present, audios and videos are the most common methods in ADD. The Audio-Visual Emotion recognition Challenge (AVEC), which plays an important role in affective computing, has also been considered as a major challenge in depression recognition [11]. Researchers usually extract cues of visual from temporal dynamics of facial expression, eye movements, head movements, and gestures. Acoustic features are extracted by the vocal dataset including prosodic features, source features, formant features, and spectral features. Physiological signals are also an important method in ADD [12]. In addition, some studies analyzed the text and identified depressed people through twitter data etc. [13].

Recent studies revealed that gait can provide more useful information on depression detection [14]. For example, gait conveys information about the walker's emotion [15], [16] including depression and anxiety [17], [18]. In [19], the authors extracted a series of 3D poses from the RGB video of an individual walking and used the gait features to classify four kinds of emotions. In [20], the Kinect was used to extract the skeleton information of the participants, and Fast Fourier Transforms was used to analyze the spectrum features of gait data for classifying different emotions. Therefore, in this paper, we also use gait information for ADD.

B. Skeletal representation

A few studies have focused on gait skeleton representation for depression detection. These studies always used raw data,

including all the joints, which may include uninformative or redundant data and increase the processing time.

There are several reports on the representations of skeleton sequences for specific human motion in pattern recognition. In [21], the authors put forward that the seven joints of the torso can be regarded as a rigid body in the process of human movement. Then, the authors used this estimate to represent the remainder of the human skeleton in relative manner. Furthermore, the studies in psychology on biological movements showed that a few joints were enough to provide information for accurate recognition [22]. In [20], the authors referred to the application of Troje's virtual marker model [23] in psychology and the principle of simplification. It presented a skeleton representation, which contained 14 joints (all 25 points), to analyze the gait patterns for emotion recognition. By using Kendall's shape framework, Hosni et al. [24] proposed a space-time representation of 3D gait-related skeletal sequences for gait recognition.

III. METHOD

A. Dataset

The depression gait dataset in postgraduate students is used in this study, comprising 274 unsegmented sequences depicting 95 individuals. All the individuals are divided into two groups based on Patient Health Questionnaire (PHQ-9, Chinese version) [26] score (score ≥ 10) and Zung Self-rating Depression Scale (SDS, Chinese version) [27] score (score ≥ 60). The non-depressed group (M:28, F:24) has 136 fragments. The scored-depressed (M:23, F:20) group has 138 fragments.

During data collection, all participants were asked to walk two round trips on a 10 meters path. Two Microsoft Kinect V2 cameras were arranged above the walkway and connected to the ceiling, forming a certain angle with the ground. The camera records the gait information of the participants at a frame rate of 30Hz.

B. Data Pre-processing

1) *Angle transformation*: Considering our cameras are located in the ceiling, there is a certain angle between the Kinect camera and the ground. We need to transform the coordinate system of the raw data for analyzing precisely. We use the SpineBase joint as a reference to derive the angle between the Kinect camera and the ground. The Ordinary Least Square (OLS) is used to calculate the slope of the data. It shows the formula in Eq(1).

$$\tan \alpha = \frac{n \sum z_i y_i - \sum z_i \sum y_i}{n \sum z_i^2 - (\sum z_i)^2} \quad (1)$$

where $\tan \alpha$ is the slope between the Kinect camera and the ground, n represents the number of video frames, z_i is the value of the Z axis of the Spinebase joint, and y_i is the value of the Y axis of the SpineBase joint.

After the angle is obtained between the camera and the ground, each frame of data is multiplied by a transformation matrix, as shown in Eq(2). It shows the results in Figure 2.

$$\begin{bmatrix} x' & y' & z' \end{bmatrix} = \begin{bmatrix} x & y & z \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos \alpha & \sin \alpha \\ 0 & -\sin \alpha & \cos \alpha \end{bmatrix} \quad (2)$$

where $[x' \ y' \ z']$ is the joint position after coordinate transformation; $[x \ y \ z]$ is the raw data; α is angle between the Kinect camera and the ground.

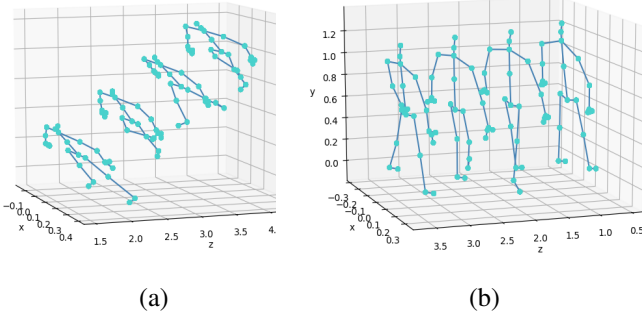


Fig. 2: The raw data before and after angle transformation.

2) *Re-sampling and De-noising*: We use the Gaussian Filter to smooth the data, reduce high-frequency noise [28]. The length of Gaussian filter window is 5 and the convolution kernel $1/16*[1,4,6,4,1]$. It can filter the x-axis, y-axis and z-axis data respectively according to the timestamp. We only analyze skeleton front view to obtain precise features. Meanwhile, the Fast Fourier Transform required a data length equal to the power of 2. So, we keep 64 frames of each fragment.

C. Rigid-body representation

Previous work verified some differences in gait between depressed and healthy individuals [17], [25]. We find that this difference tends to fasten on specific body parts, such as limbs, head, and shoulders. It means that these joints contribute significantly to the depression recognition in gait, while other joints contribute less, such as spine and hip.

Besides the above clinical studies of gait abnormality in depressed patients, we want to quantify the contribution of each joint in gait movement. In [29], the authors calculated joint weights based on the volumes and areas formed between the limbs and the main body at the frame level. In this paper, the mechanical energy of gait is defined to denote the kinematic information of each joint. The mechanical energy of object is given by Eq.(3).

$$E_j^f = E_{k,j}^f + E_{p,j}^f \quad (3)$$

where $E_{k,j}^f$ and $E_{p,j}^f$ are the kinetic energy and potential energy of the j th joint in f th frame. Similar to [30], a gait neutral pose (GNP) is defined as a simulated standing pose with two arms being rested on the side of thighs and two legs being straight and unbent. In particular, a gait neutral pose is

treated as a special frame when the normal of a plane formed by the torso parallel to the Z-axis in the instant poses, and its joint positions as reference ones. So, different individuals have their own gait neutral pose. Figure 3 shows example instant poses and their pseudo neutral poses. We assume all joints in the human body have the same mass and ignore the gravitational acceleration constant. The entire skeleton mechanical energy is obtained by Eq.(4).

$$E_j^f = \frac{1}{2} \sum_{f=1}^n \left(\frac{p_j^f - p_j^{f-1}}{\Delta f} \right)^2 + \sum_{f=1}^n (p_j^f - GNP_j) \quad (4)$$

where, p_j^f, p_j^{f-1} are the joint j positions at frame f and frame $f-1$, GNP_j is the corresponding joint positions in a gait neutral pose, n is the number of frames, Δf is one frame.

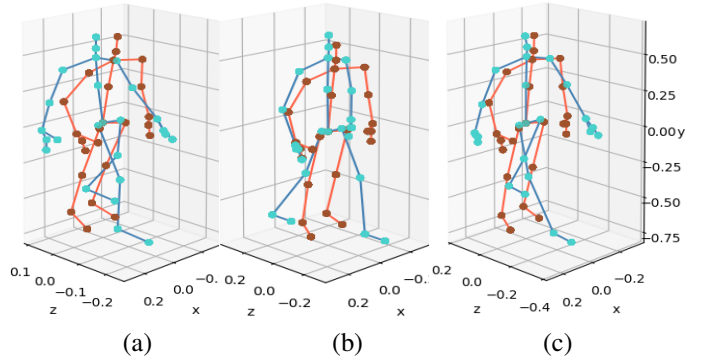


Fig. 3: Comparison of instant poses (steelblue lines) and their corresponding pseudo neutral poses (sienna lines) in different individuals.

One can observe that the color of each part of the human body is different in Figure 4, the darker bone color, and the greater mechanical energy. This is consistent with previous clinical findings that the major motor abnormalities in depressed patients focus on limbs and shoulders. The amplitude of torso and head are very small. However, due to multiple observations in clinical practice, depression patients have smaller vertical head movement and more slouching head posture. It is proved that the head is the key part in depression recognition, so we keep the head joint in the subsequent skeletal model construction. We also observe that the joint of the trunk (defined triangle by 5 skeletal joints as illustrated in Figure 4) moves as a whole during walking. We define the five joints as the torso. The movement period of the torso is almost the same, and the amount of activity at these five joints is the lowest among all joints. Thus, the torso can be regarded as a rigid body, all joints use rigid body as a center and re-estimate position.

We find that limb joints tend to be inaccurately detected and tracked, especially for the hands and feet, this often leads to generating noisy 3D joint position data. In order to make the measurement more precise and remove unnecessary joints, we take the average value of the left wrist (joint 6) and other three joints (7, 21, 22) in left hand, while the left ankle (joint

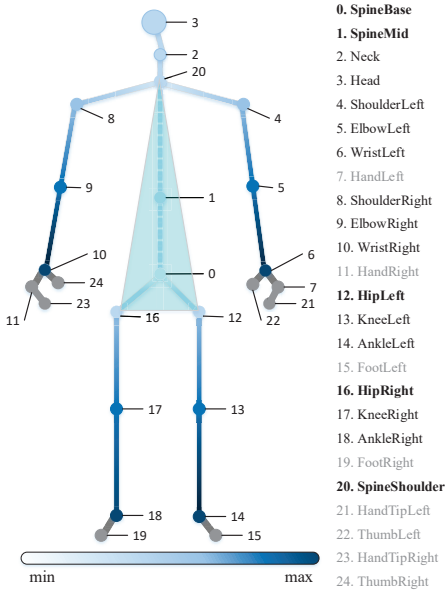


Fig. 4: The diagram of joints energy.

14) and left foot (joint 15) are also averaged. Similar process is applied to the right arm and leg. It shows the joints deleted after averaging in gray in Figure 4.

We merge the five joints (0,1,12,16,20) together and call them the torso joint. Using the torso as the center of mass of the human body, we recalculate the values of each joint. First, we average the five joints (0,1,12,16,20) to get the position of the torsoBase joint. Then, the joints of the upper and lower limbs minus the torsoBase joints. The process is shown in algorithm 1.

Algorithm 1 re-estimate joints position

Input:

segments[n][17*3], n is the number of frames;

Output:

new_segments[n][12*3];

1: **for** each $i \in [0, n - 1]$ **do**

2: torsoBase = (segments[i][SpineBase] + segments[i][SpineMid] + segments[i][SpineShoulder] + segments[i][HipLeft] + segments[i][HipRight]) / 5 ;

3: **for** each joint $\in 2, 3, 4, 5, 6, 8, 9, 10, 13, 14, 17, 18$ **do**

4: new_segments[i][joint] = segments[i][joint] - torsoBase;

5: **end for**

6: **end for**

After the above processing, the rigid-body representation with 12 joints is established. The clinical depression's gait abnormality and kinematic characteristics of gait were fully considered in the process of model construction, therefore, the rigid-body representation is very suitable for ADD, and can remove redundant information and reduce the classification time cost.

D. Features extraction and Classified method

We use the method that is proposed by Li et al. [28] to extract gait features using Fast Fourier Transforms (FFT). The formula is shown in Eq(5). According to the formula, we can extract 64 features from each joint. To improve predictive accuracy and minimize the error caused by redundant information. We compare the relationship between the number of different features and accuracy, and select the 20 features with the largest absolute value from a different axis. For example, a total of $20 \times 3 \times 12$ features is used for each participant after using rigid-body representation.

$$X_k = \sum_{n=0}^{j-1} A_j e^{-i2\pi k \frac{j}{n}} \quad k = 0, \dots, n-1 \quad (5)$$

where X_k is extracted features, A_j is different axis ($A \in \{X, Y, Z\}$).

Then we use the Principal Components Analysis (PCA) to reduce the dimensionality of the data. We choose several commonly used classifiers in machine learning to build our model, i.e., SVM, Linear Discriminant Analysis (LDA) and K-Nearest Neighbor (KNN), some of which have been successfully applied to clinical gait analysis [31], [32].

In order to evaluate the performance of the classifiers and to simulate the reality of real depression recognition as much as possible, we adopt a leave-one-out cross-validation (LOOCV) strategy. For our dataset, the 'leave-one-out' protocol is adopted, keeping the minimum subject subset containing all the segments of a person as test set and employing all the others for training.

IV. EXPERIMENT RESULTS AND DISCUSSION

A. Rigid-body representation experimental results

To verify the validity of the rigid-body representation, we use two sets of data for experiments. One set is raw data with 19 joints on each frame. The other is the data with rigid-body representation with 12 joints on each frame. In Table I, accuracy, sensitivity, specificity, and F-score are presented.

According to the data in Table I, we can observe that after rigid-body skeletal representation is adopted, the accuracy on classification is generally improved by an average of 8.30%. At the same time, we find that specificity, sensitivity, and F-score of the three classifiers improve significantly after using the rigid-body representation model. We also note that after rigid-body representation is adopted, it reduces the computation time on classification.

The results show that combining behavioral characteristics in our proposed skeletal model can provide better classification performance in depression recognition in gait.

B. Compare with different methods

In order to better evaluate our method, we also compare with other methods, and use SVM as a classifier. However, the methods of depression recognition in gait have not been well established yet. Therefore, we refer to the rigid representation methods in other area. The authors have referred to a skeletal

TABLE I: Classification results of rigid-body representation and others representation.

		Accuracy	Sensitivity	Specificity	F1-score
Raw	KNN	0.7265	0.9817	0.5040	0.7698
	SVM	0.8462	0.8807	0.8160	0.8421
	LDA	0.7436	0.7615	0.7280	0.7345
Rigid-doby	KNN	0.8077	0.9541	0.6800	0.8221
	SVM	0.8889	0.9083	0.8720	0.8839
	LDA	0.8120	0.8165	0.8080	0.8018

representation using only the upper or lower limbs [25], [33]. Therefore, we also use this method to train the participants' upper and lower body separately. In [34], the author proposed the concept of position vectors and conducts gait analysis through position vectors. Therefore, we apply this method on our dataset. In Figure 5, the best accuracy, sensitivity, specificity, and F-score are presented in different skeletal representation method.

We can observe that our method significantly higher in accuracy than other skeletal representation methods. The F-score is the highest of all methods, which also shows that our method is more effective. Compared with other methods, our method achieve better performance than the above methods.

C. Discussion

This article provides a new idea for ADD. Our method has the following advantages. First, data collection is easy. The gait data collection process need not contact the participants' body and does not need special data acquisition devices. Second, simple data processing. Gait data in our method are extracted from the skeleton data of the participants by Kinect in real time. Both the amount of data and the difficulty of processing are greatly reduced and can be developed towards real time detection. Third, low cost. The collection of gait data does not require a special device, and the camera can be easily obtained for collecting data. With small capital investment, it can achieve good detection results. However, the experimental results show that the detection accuracy need further improved. Our method is no obvious difference in detection accuracy from other methods, such as audio, video, and EEG.

For rigid-body representation, combining joint energy based on the kinetic and potential energy and clinical experience, we simplify the joints and minimize the error caused by redundant information. Yet, the reduction of the amount of data does not mean the loss of effective data. This means that the information we deleted may carry a lot of redundant and irrelevant information. In particular, there are large errors in the data of the hands and feet, which affect the classification results. The movement period of the torso joints is almost the same, and it does not affect the final classification result after removing these joints. We find that after using the rigid-body representation, the specificity improved significantly, which means that the model has a better ability to distinguish negative examples.

According to the above discussion, our method has the advantages of reliable results, simple data collection, fewer data processing time and less capital investment. The rigid-body representation proposed method provides new ideas for ADD and is more suitable for practical application scenarios.

V. CONCLUSION

In this paper, a novel framework is proposed for classifying depressed and non-depressed groups from the non-intrusive gait data collected by Microsoft kinetic. We use OLS to calculate the slope of the data, which can help us better fit the actual movement of the participants. Different from existing methods, a rigid-body representation for depression in gait is developed, which effectively captures gait abnormality and joint energy based on the kinetic and potential energy. This representation can decrease the data processing time and improve classification efficiency. Experimental results show that the proposed method is effective in characterizing and recognizing depression.

The above research shows the potential of gait analysis to develop non-intrusive and low-cost methods for monitoring depression in real-time. It could serve as a convenient and objective auxiliary tool for detecting depression in its early stage.

ACKNOWLEDGMENT

This work was supported in part by the National Key Research and Development Program of China (Grant No. 2019YFA0706200), in part by the National Natural Science Foundation of China (Grant No.61632014, No.61627808, No.61210010), in part by the National Basic Research Program of China (973 Program, Grant No.2014CB744600), and in part by the Program of Beijing Municipal Science & Technology Commission (Grant No.Z171100000117005).

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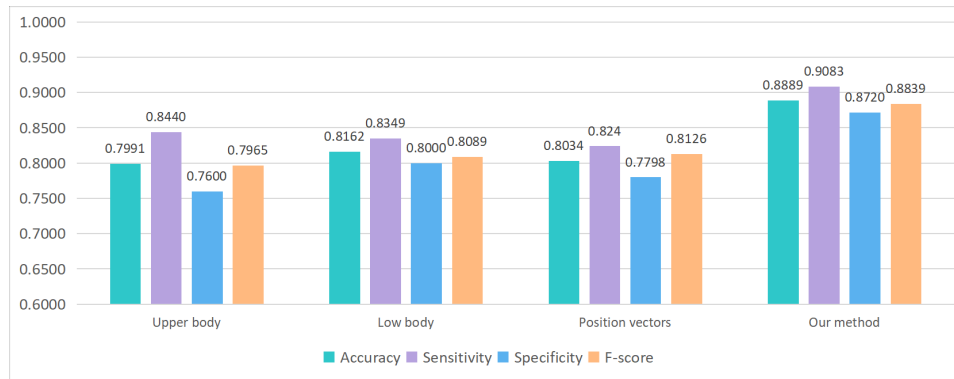


Fig. 5: Comparisons with other methods.

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