Evaluating the Effect of Various Walking Conditions on KINECT-based Gait Recognition

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Abstract: Human gait is one of the unobtrusive behavioral biometrics that has been extensively studied for various commercial and government applications. Biometric security, medical rehabilitation, virtual reality, and autonomous driving cars are some of the fields of study that rely on accurate gait recognition. While majority of studies have been focused on achieving very high recognition performance on a specific dataset, different issues arise in the real-world applications of this technology. This research is one of the first to evaluate the effects of changing walking speeds and directions on gait recognition rates under various walking conditions. Dataset was collected using the KINECT sensor. To draw an overall conclusion about the effects of walking speed and direction to the sensor, we define distance features and angle features. Furthermore, we propose two feature fusion methods for person recognition. Results of the study provide insights into how walking speeds and walking directions to the KINECT sensor influence the accuracy of gait recognition.

Keywords: Gait Recognition, Kinect Sensor, Feature Fusion, Walking Conditions, Biometric Security

1 Introduction

Human gait is one of unobtrusive behavioral biometrics that has been extensively studied for various commercial and government applications. Biometric security, medical rehabilitation, virtual reality, autonomous driving cars are some of the fields of study that rely on accurate gait recognition. Gait is a type of an unobtrusive biometric that is very effective in recognize a person from a distance. Based on human anatomy, every person’s gait is different from another based on their body size, the length of the bone structure and preferred walking style [10]. Thus, gait is a highly distinctive feature which makes it suitable for human recognition at the distance. It can be captured naturally without individual’s collaboration or awareness. Another advantage of gait as a biometric is that it is difficult to hide or imitate someone’s gait, so it can be effectively used as an identity solution in commercial surveillance systems. While the majority of studies has been focused on achieving very high recognition performance on a fixed dataset, different issues arise in the real-world applications of this technology [4, 16]. Our work is one of the first to evaluate the effects of changing walking speed and directions on gait recognition rates under various conditions. KINECT sensor v2 was used to obtain gait samples. In order to draw an overall conclusion about the effects of walking speed and direction toward the sensor, we define distance features, angle features and consider two feature fusion methods. Results of the study provide insights on how walking speed and walking direction in respect to the KINECT sensor influence the accuracy of gait recognition. The paper is structured as follows. Section 2 presents a brief literature review of gait recognition methods. Section 3 introduces a complete Kinect based gait recognition workflow. In section 4, experimental results and analysis of the Kinect gait recognition system under different scenarios are discussed. Section 5 concludes this paper with a discussion of obtained results and future work.

2 Literature Review

In the past, gait recognition mostly relied on video cameras to capture the movement of a person [11, 14]. But this kind of data collection requires significant preprocessing efforts as well as extensive storage capacity. After Microsoft Kinect was first introduced as a peripheral of Xbox 360 gaming console, collecting, storing and processing of gait data was significantly simplified. Kinect can provide the data stream of walking movement when an SDK is used to extract human body joint data during gait cycle.

Kinect is a low-cost consumer-based depth sensor, that is sensitive to noise and effect of data sampling environment. Thus, some external factors may easily influence the performance of gait recognition based on Kinect [12]. For example, if someone walks in an uneven speed, coordinates of human skeleton joints may not be captured accurately by the device. Also, if someone does not follow exact same trajectory, the walking pattern may be different even for the same person [8]. Both situations will have effects on the feature extraction and gait recognition accuracy. Thus, it is very important to study how walking speed and direction influence gait recognition performance in order to gain an insight on what environmental factors should be considered when deploying a gait recognition system in real life.

Recently, a lot of attention is given to incorporating deep learning paradigms in the gait recognition. Both Convolution Neural Networks and Graph Based Neural Network architectures has been explored [5, 15, 17]. For example, authors of [17] proposed KinectGaitNet to model the 3D input representation with convolutional neural network. It can achieve a high accuracy and shorter inference latency via the unique 3D input representation of joint coordinates. However, even this research rarely addresses varied speed and research direction effect on the overall recognition rates.

The contributions of this research are as follows. In order to evaluate the effects of different speeds and directions in each step of gait recognition, we developed a fully functioning gait recognition system utilizing score-level and rank-level fusion methods. During the gait cycle detection, we adopted and modified three distance parameters, that are commonly used in gait recognition studies based on Kinect. These modified parameters were proven to be highly efficient for gait recognition task. During feature extraction, we defined both distance features and angle features, as we postulated that the speed and directions of the walk affects length and angle features differently. During model training and classification period, we performed two types of distance measurements, corresponding to distance features and angle features, using K-nearest neighbor as the classification method. Finally, we compared the obtained recognition rate and statistical parameters corresponding to the walking conditions. We compared gait recognition performance under different walking speeds and directions. To the best of our knowledge, this is the first in-depth study on how walking direction and speed directly affect Kinect gait recognition accuracy.

3 Methodology

The gait recognition method proposed in this paper follows the gait recognition five-steps model, customized with proposed gait features and information fusion methods. After obtaining the data stream from the Kinect version 2, which contains coordinates of 25 joints in three directions, we pre-process the data with data filtering method, based on local regression with weighted linear least squares [7]. Next, the sequence of processed data is divided into several complete gait cycles. After that, static features and dynamic features are extracted from the processed data for further matching. Finally, the

K-Nearest Neighbor classification method [7] is used to classify the testing samples and calculate the final recognition rate.

As the goal of the paper is to evaluate the effects of walking speeds and directions on the performance of gait recognition, a thorough comparison of results under different conditions was performed. Also, different methods during each stage of the gait cycle are compared under all the conditions in order to find out which kind of method is suitable for a specific condition.

To be more specific, the three types of walking speeds are defined as slow, normal and fast. In addition, six types of walking directions are considered: forward, backward, zigzag, zigzag-parallel, parallel and round. The normal speed and the forward direction are set to be the correct speed and direction in control groups when a comparison is made.

3.1 Data Collection

Kinect can capture RGB images, depth images of a scene and skeleton data streams in real time. However, the proposed method only uses skeleton data stream from Kinect v2 to construct the dataset. Three sequences corresponding to the data captured under eight scenarios with frame rate fixed at 30 frames per second (fps). In total, the dataset contains 168 sequences (24 sequences for each person). Skeleton joints considered demonstrated in Table 1. All scenarios of different speed or direction conditions for each person are listed in Table 2. The scenario 1-3 of this table are designed to evaluate the effect of speed conditions with the direction fixed as forward. In the same way, the scenarios 3-8 of this table correspond to the evaluation of walking direction with speed fixed as normal. For each repeated dataset collected for the same subject, the ground truth of how many steps the subject takes was recorded in a TXT file with one row and 8 columns corresponding to eight scenarios.

3.2 Pre-processing

3.2.1 Proper Distance between the Kinect and the Subject

Because the accuracy of Kinect capturing joint positions may be reduced when a subject is farther from the sensor, a proper distance between the Kinect and the subject should be considered. We compare the height of a person calculated from the joint coordinates with the ground truth height recorded separately. For the i^{th} frame of a sequence, Da,bi acts as the distance between the two joints Ja and Jb. The joints are defined in Table 1. Then the height in the ith frame can be computed as:

$$H^i = D_{1,2}^i + D_{2,3}^i + D_{3,4}^i + \max(D_{5,7}^i + D_{7,10}^i, D_{6,8}^i + D_{8,11}^i) \quad (1)$$

As shown in Fig.1, a suitable distance for gait collection using Kinect is 1.5m-4.2m. Therefore, the data out of this range is not considered in our experiments.

3.2.2 Data Smoothing

The weighted local regression method is applied to smooth the data [7]. The regression weights for each data point in the span are calculated as shown below. Here, x acts as the predictor of the original value, while xi represents the closest neighbor of x within the span. Then, the distance between x and the most distant predictor value within the span is defined as d(x). Finally, we can get the smoothed value with less noise data after weighted regression:

$$w_i = \left(1 - \left|\frac{x - x_i}{d(x)}\right|^3\right)^3 \quad (2)$$

Table 1 Skeleton Joints Considered

Joint Name	Head	neck	Spine Shoulder	Spine Base	Hip Left	Hip Right	Knee Left	Knee Right	Ankle Left	Ankle Right
Joint Number	J_1	J_2	J_3	J_4	J_5	J_6	J_7	J_8	J_{10}	J_{11}

Table 2　Scenarios of Data Collection

Condition Scenario	Speed			Direction					
	Slow	Fast	Normal	Forward	Backward	Zigzag	Zigzag-p	Parallel	Round
1	√			√					
2		√		√					
3			√	√					
4			√		√				
5			√			√			
6			√				√		
7			√					√	
8			√						√

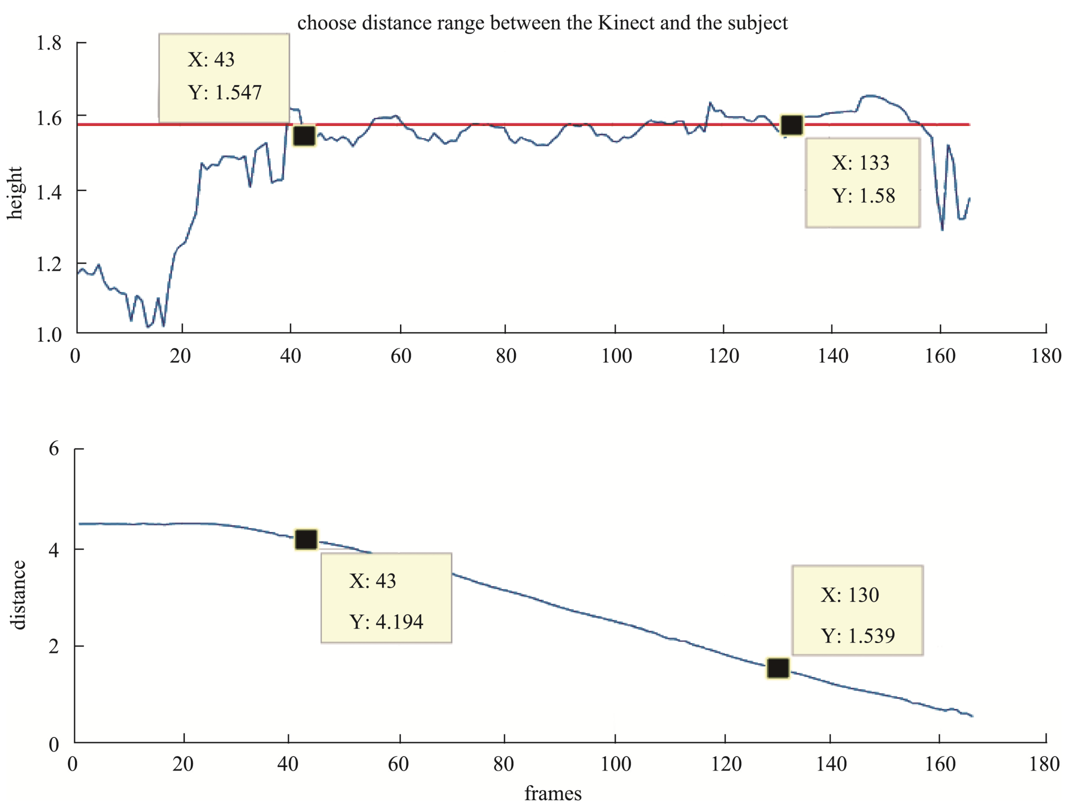

Fig.1　Proper Distance Range between the Kinetic Sensor and the Subject

3.3　Gait Cycle Detection

Gait cycle detection is an important part of any gait recognition research as a complete gait cycle provides enough information to extract salient features. Mainly there are three kinds of variables defined in the classical machine-learning based gait recognition research.

A method of detecting foot-off and foot contact with knee angle for gait cycle separation was proposed in 2017 [2]. In 2014, Chattopadhyay and his colleagues [6] proposed the absolute depth difference in limbs as the absolute separation between the left and right limbs along the Z axis of the Kinect coordinate system. Another way to detect gait cycle is explained in [1] with the distance of right ankle and left ankle to detect a complete gait cycle. In this section, we discuss these three existing methods and propose a modified method based on the work by [2].

1) Knee angle: The knee angle is calculated from the coordinates of the right hip, right knee and right ankle (Fig.2) according to [2]:

$$\mathrm{D}_1 = \frac{\overrightarrow{KH} \cdot \overrightarrow{KA}}{|\overrightarrow{KH}| \cdot |\overrightarrow{KA}|} \tag{3}$$

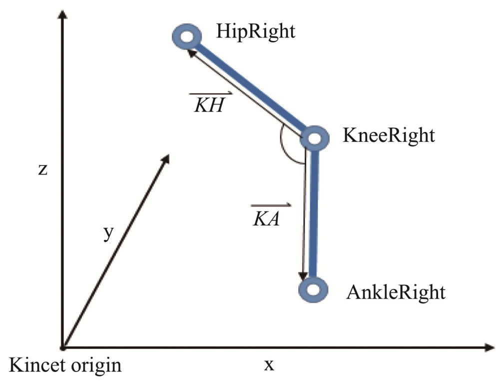

Fig.2 Knee Angle as Parameter to Detect

2) Absolute depth distance in limbs: The definition is of the summation of relative distance between the left and right limbs in the Z-axis direction of the Kinect coordinate system. In this equation, zra and zla represent the depth values of coordinates of right ankle and left ankle in Z-axis, and zrw and zlw show the depth values of coordinates of right wrist and left wrist in Z-axis accordingly. Afterwards the D_2 is calculated by summing the two distances up:

$$D_2 = |Z_l^w - Z_r^w| + |Z_l^a - Z_r^a| \tag{4}$$

It can be noticed in Fig.3 (a, b) that D2 is as periodic as pattern of walking cycle in normal cases. However, in round and other parallel scenarios, this cyclical period is not stable enough for gait cycle detection.

3) Distance between ankles: This distance is calculated as the distance between the left ankle and the right ankle:

$$D_3 = \sqrt{(X_l^a - X_r^a)^2 + (Y_l^a - X_r^a)^2 + (Z_l^a - Z_r^a)^2} \tag{5}$$

We introduce a new method based on absolute depth difference in limbs. This method is calculating the distance in 3-dimension axis instead of in only Z-axis, as shown in Formula 6. The Xlw denotes the coordinate of left wrist in X-axis. This improved method is named as Improved Absolute Distance (IAD). Fig.3(c) shows that this method has a more stable cyclical period than the original one, compared to Fig.3(b). This helps to increase the accuracy of gait cycle detection.

$$\mathrm{D}_4 = \sqrt{(X_l^w - X_r^w)^2 + (Y_l^w - X_r^w)^2 + (Z_l^w - Z_r^w)^2} + \sqrt{(X_l^a - X_r^a)^2 + (Y_l^a - X_r^a)^2 + (Z_l^a - Z_r^a)^2} \tag{6}$$

In order to keep the condition as only variance during our evaluation, we choose the same cycle detection method in all feature extraction work. After that, we chose three minima to identify a complete gait cycle. This way there are several gait cycles in the same data sequence.

3.4 Extraction of Biometric Features

Body features extracted from Kinect are usually divided into static features and dynamic features. In this proposed method, the characteristics of static and dynamic features are combined, so the features are mainly divided into distance features and angle features, as shown in Fig.4.

3.4.1 Distance Features

Distance features consist of two kinds of features and their variances: length features and relative features. Both distance features are calculated with Euclidean Method. Formula 7 depicts this computation with n denoting 28 features. The distance feature F is defined by Formula 8. Here, Fl represents ten length features. Flv refers to ten variances of each length feature. Fr is defined as the four relative features. Frv acts as the four variances of each relative feature. In Fig.4, blue lines show ten length features and red lines show four relative distance features.

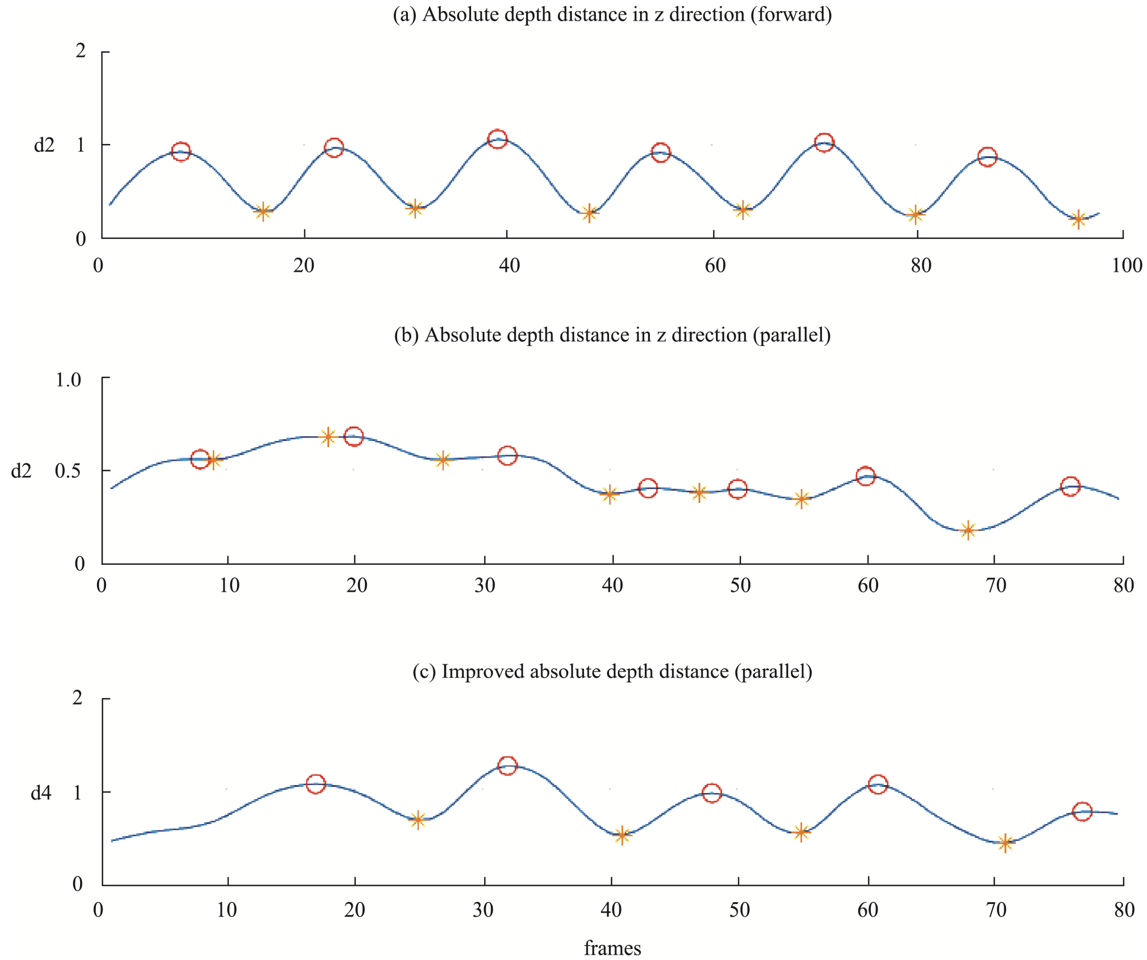

Fig.3 Parameters for Gait Cycle Detection

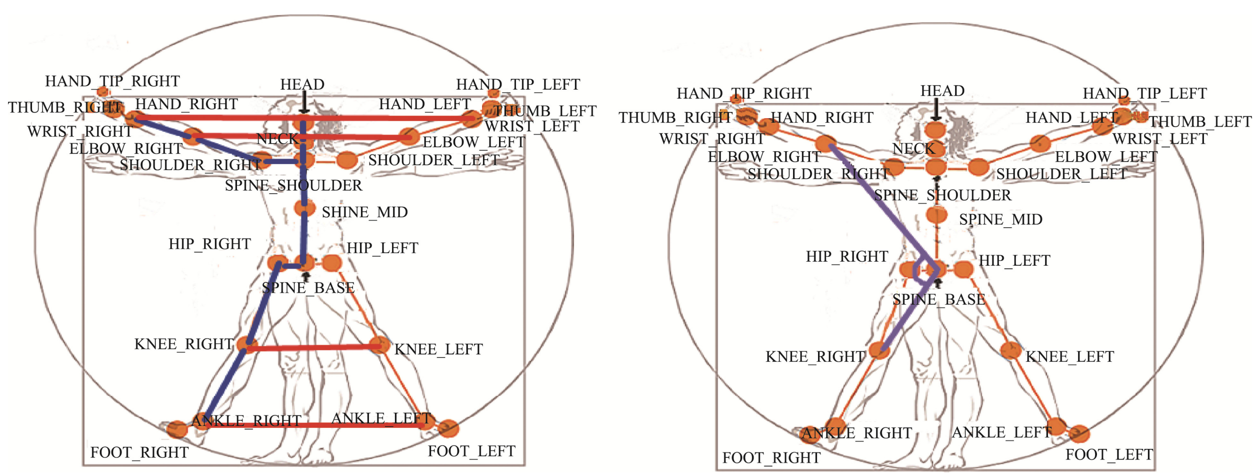

Fig.4 Distance Features and Angle Features

$$\mathrm{d(p,q)} = \sqrt{\sum_{i=1}^{n}(p_i - q_i)^2} \tag{7}$$

$$\mathrm{F} = \{F_l, F_{lv}, F_r, F_{rv}\} \tag{8}$$

$$F_l = (l_1, l_2, l_3, l_4, l_5, l_6, l_7, l_8, l_9, l_{10}) \tag{9}$$

$$F_{lv} = (lv_1, lv_2, lv_3, lv_4, lv_5, lv_6, lv_7, lv_8, lv_9, lv_{10}) \tag{10}$$

$$F_r = (r_1, r_2, r_3, r_4) \tag{11}$$

$$F_{rv} = (rv_1, rv_2, rv_3, rv_4) \tag{12}$$

3.4.2 Angle Features

The angle features are defined as the angles formed by the corresponding two joints with respect to a reference point Spine. Based on results of research of [1], twenty relative joint-pairs angles are most distinctive, and thus they are chosen as shown in Table 3.

Table 3 Angle Features

Number	Joint 1	Joint 2
1	HipRight	WristLeft
2	HipRight	HandLeft
3	HipRight	HandTipLeft
4	HipRight	ThumbLeft
5	HipLeft	WristRight
6	HipLeft	HandRight
7	HipLeft	HandTipRight
8	HipLeft	ThumbRight
9	ThumbRight	WristLeft
10	ThumbRight	HandLeft
11	ThumbRight	HandTipLeft
12	ThumbRight	ThumbLeft
13	ThumbLeft	WristRight
14	ThumbLeft	HandRight
15	ThumbLeft	HandTipRight
16	WristRight	WristLeft
17	WristRight	HandLeft
18	WristRight	HandTipLeft
19	HandRight	HandLeft
20	HandLeft	AnkleLeft

3.4.3 Feature Fusion

The fusion methods are highly useful during matching stage. The score-based method in Fig.5 demonstrates how the final fusion score is calculated from the different kinds of DTW features. As for distance features, the score is calculated with the Euclidean distance between an observation of 28-dimensional distance features in training set and testing set. The score for each angle feature is calculated with Dynamic Time Warping [9]. This is well-known non-linear sequence alignment method, which is originally proposed in [13] for speaking signal alignment. It is used to measure the dissimilarity between two given gait samples without any intermediate resampling stage for the same length gait sequences. After obtaining two scores of distance features and angle features, one generally cannot directly combine these scores in a statistically meaningful way because these scores have different ranges and distributions. Therefore, it is necessary to transform them to be comparable before fusion. In this proposed method, we utilize a linear normalization method for scaling all the distances between 0 and 1.

$$\mathrm{Nomalized}(x_i) = \frac{x_i - \min(X)}{\max(X) - \min(X)} \tag{13}$$

Rank-based fusion is a way to make a final decision by the overall rank, which is summed by several sorting results of distances between observations in training set and testing set as mentioned above. This is similar to a majority voting scheme in which the final prediction of an observation is assigned to the class most common among its k nearest neighbors (as shown in Fig.6).

3.5 Classification

In this study, the k-nearest neighbor method is applied to accomplish the classification process. The distance measurement is Euclidean Distance for classification based on the distance features, where Dynamic Time Warping is used to measure the dissimilarity in recognition based on angle features. The values of features are standardized by centering and scaling with column mean and standard deviation.

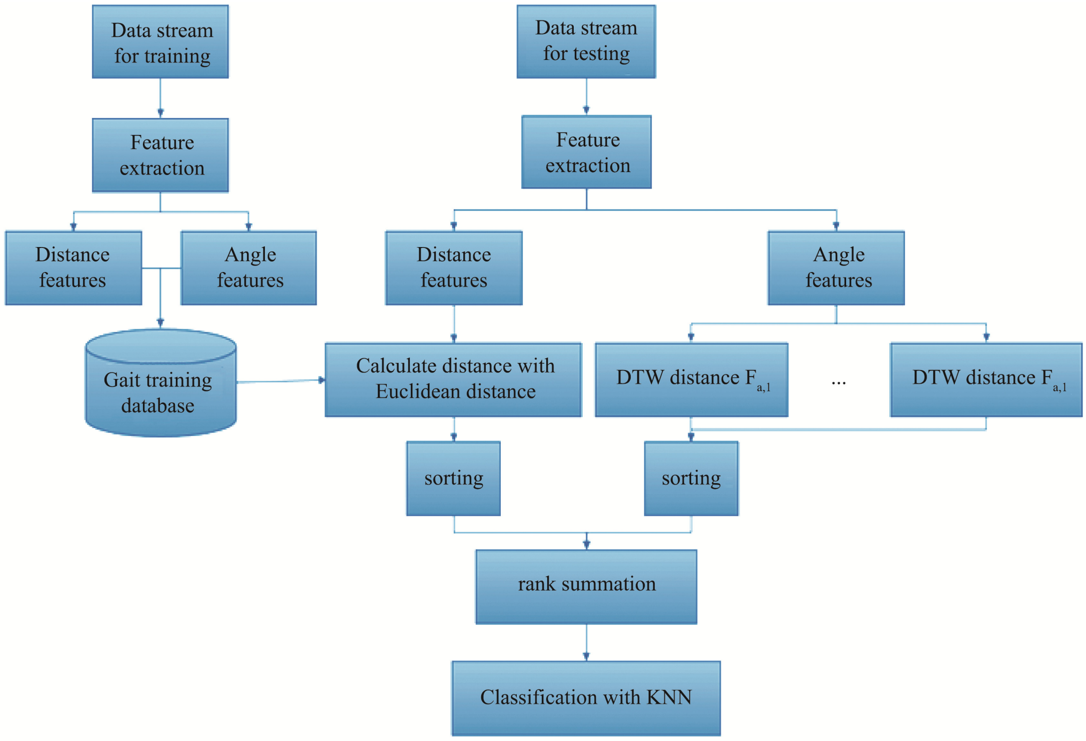

Fig.5 System Architecture with Score-level Fusion

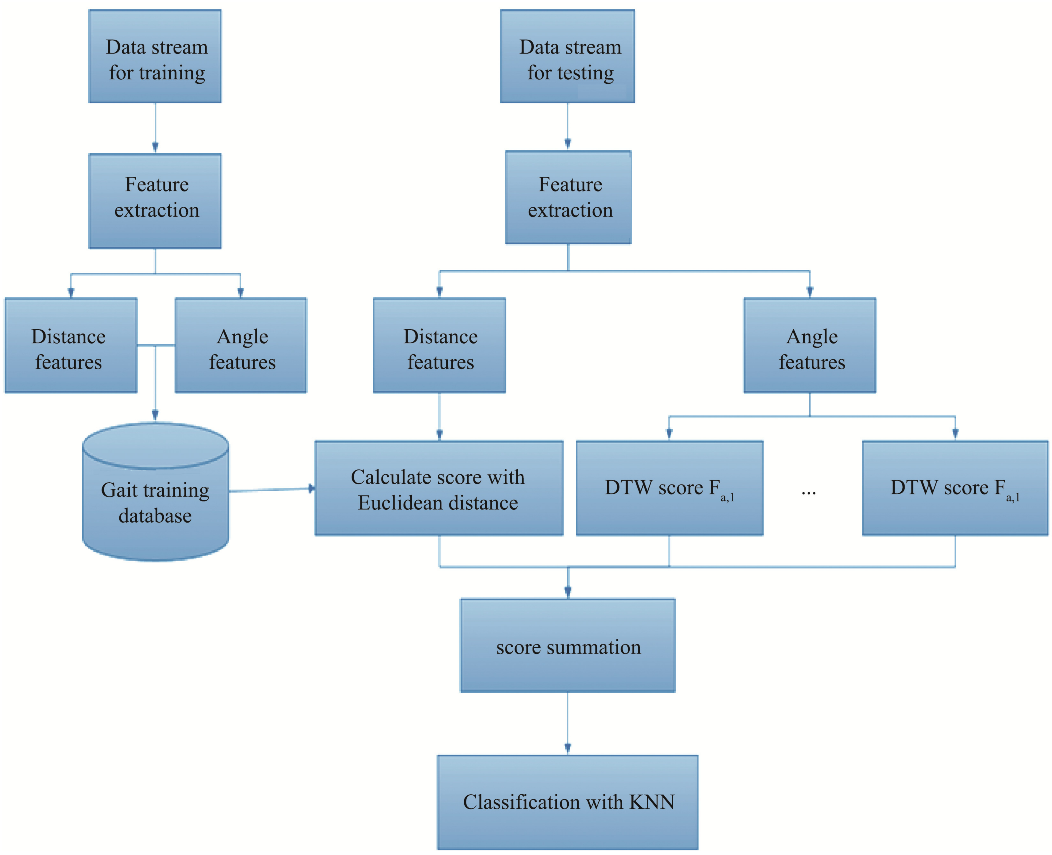

Fig.6 System Architecture with Rank-level Fusion

This is demonstrated by Formula 14, where x acts as the original value, μ represent the mean value of each column and σ is the standard deviation:

$$\text{Standardized}(x) = \frac{x-\mu}{\sigma} \tag{14}$$

When using the KNN classifier, the accuracy varies with the value of k. If the data is noisy, the accuracy of KNN classifier will diminish when k is small. However, some studies showed that [3, 8] the performance of gait recognition is best when k is equal to 1. Thus, in the comparison of recognition rates at different speeds or in various directions, 1-NN is performed.

4 Experimental Results

In this section, we present our evaluation results. Experimental scenarios and area with variant directions are shown in Fig.7 and Fig.8.

4.1 Recognition Rate

In order to obtain results with training set and testing set in different scenarios, the cross-validation was performed. The training set is the randomly selected 80% of the whole dataset. The remaining 20 % is considered as a testing set. The recognition rate is computed as the percentage of correct predicted observations in the testing set. Table 4 and Table 5 display the recognition rates in different speeds and

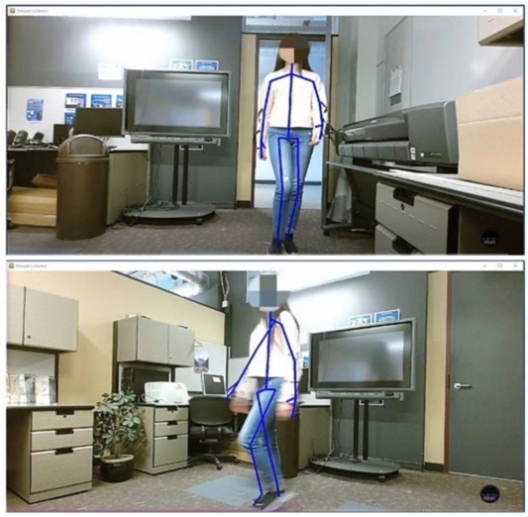

Fig.7 Experimental Scenarios

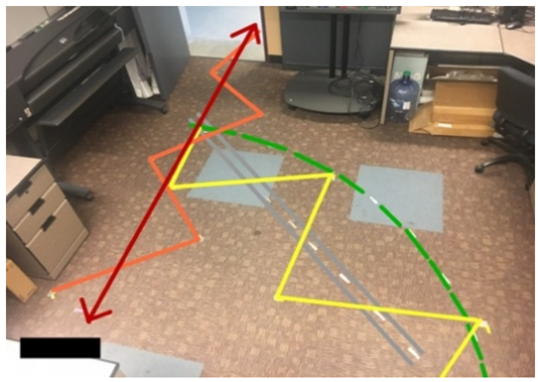

Fig.8 Experimental Area with Variant Walking Directions

Table 4 Recognition Rates at Different Speed

Test / Train	Slow			Fast			Normal		
	d	a	f	a	d	f	d	a	f
Slow	97.3	97.3	93.7	85.7	50.0	75.7	100	52.6	93.6
Fast	67.6	18.9	74.1	100	92.9	98.7	100	52.6	89.3
Normal	91.9	64.9	89.2	85.7	71.4	94.6	100	100	85.7
All Speed	94.6	89.2	96.8	100	92.9	96.0	100	100	97.9

Table 5 Recognition Rates with Different Walking Directions

Test Train	Forward			Backward			Zigzag			Zigzag-p			Parallel			Round		
	d	a	f	d	a	f	d	a	f	d	a	f	d	a	f	d	a	f
Forward	100	100	95.7	38.9	27.8	57.6	78.1	51.2	68.8	28.3	26.4	41.4	33.3	25.0	36.5	33.3	14.3	42.3
Backward	52.6	15.8	47.3	94.4	94.4	93.5	61.0	29.3	54.0	20.8	11.3	29.1	16.7	16.7	27.0	19.1	14.3	23.7
Zigzag	94.7	68.4	77.4	66.7	5.6	63.0	87.8	70.7	96.6	32.1	17.0	40.5	25.0	16.7	46.0	42.9	14.3	38.1
Zigzag-p	68.4	15.8	54.8	38.9	11.1	60.9	53.7	17.1	55.7	81.1	41.5	87.7	41.7	8.3	49.2	57.1	14.3	57.8
Parallel	52.6	26.3	50.5	50.0	27.8	44.6	43.9	12.2	45.5	47.2	26.4	48.5	75.0	25.0	88.9	61.9	14.3	68.0
Round	42.1	15.8	45.2	33.3	16.7	48.9	36.6	16.7	40.3	47.2	24.5	50.2	58.3	25.0	54.0	90.5	23.8	93.8
All Directions	100	94.7	93.6	100	100	76.1	92.7	65.9	97.2	100	100	60.4	75.0	16.7	84.1	100	85.7	82.5

directions separately with three different features. These features are distance features, angle features and feature fusion. The recognition rates in normal scenarios are above 85.7%. This shows that the features proposed in this paper are effective for gait identification.

To examine the recognition in variable-speed scenario, the model was trained with three different speeds, as shown in Table 4. When recognition happens in variable-direction scenario in Table 5, we can observe that varied directions have much more effects than varied walking speed. Also, the recognition rate is very low when only angle features are considered. Another interesting observation is that the feature fusion does not impact too much variable-direction scenario. So training the model with more data containing different directions is recommended to enhance system recognition.

4.2 Evaluating Effects

4.2.1 Gait Cycle Detection

The performances of cycle detection are measured by the accuracy of the number of steps. The results are compared among these three methods: knee angle detection, angle distance detection and the improved method with accuracy of the number of steps. The experiments show that the fast speed will significantly reduce the accuracy of gait cycle detection, while the slow speed helps to get an accurate gait detection. When the other suffer from lower detection capability, the proposed method results in a higher detective power, especially in normal, parallel and round scenarios.

4.2.2 Comparison of Features and Variance

The effects of different conditions are evaluated with the mean values and variances of 14 distance features (1-10 correspond to 10 length features and 11-14 indicate 4 relative features). Angle feature are not included in this experiments, due to the fact that the mean values and variances of them are not that significant for gait recognition, as previously discovered.

The summary of observations from experiments can be found in Fig.9. The slower the subject walks, the smaller his relative distance features are. This observation tells us that if the applied environment is speed variable, the relative distance features should not be considered in extraction as it may cause distinction even if the two observations are from the same subject.

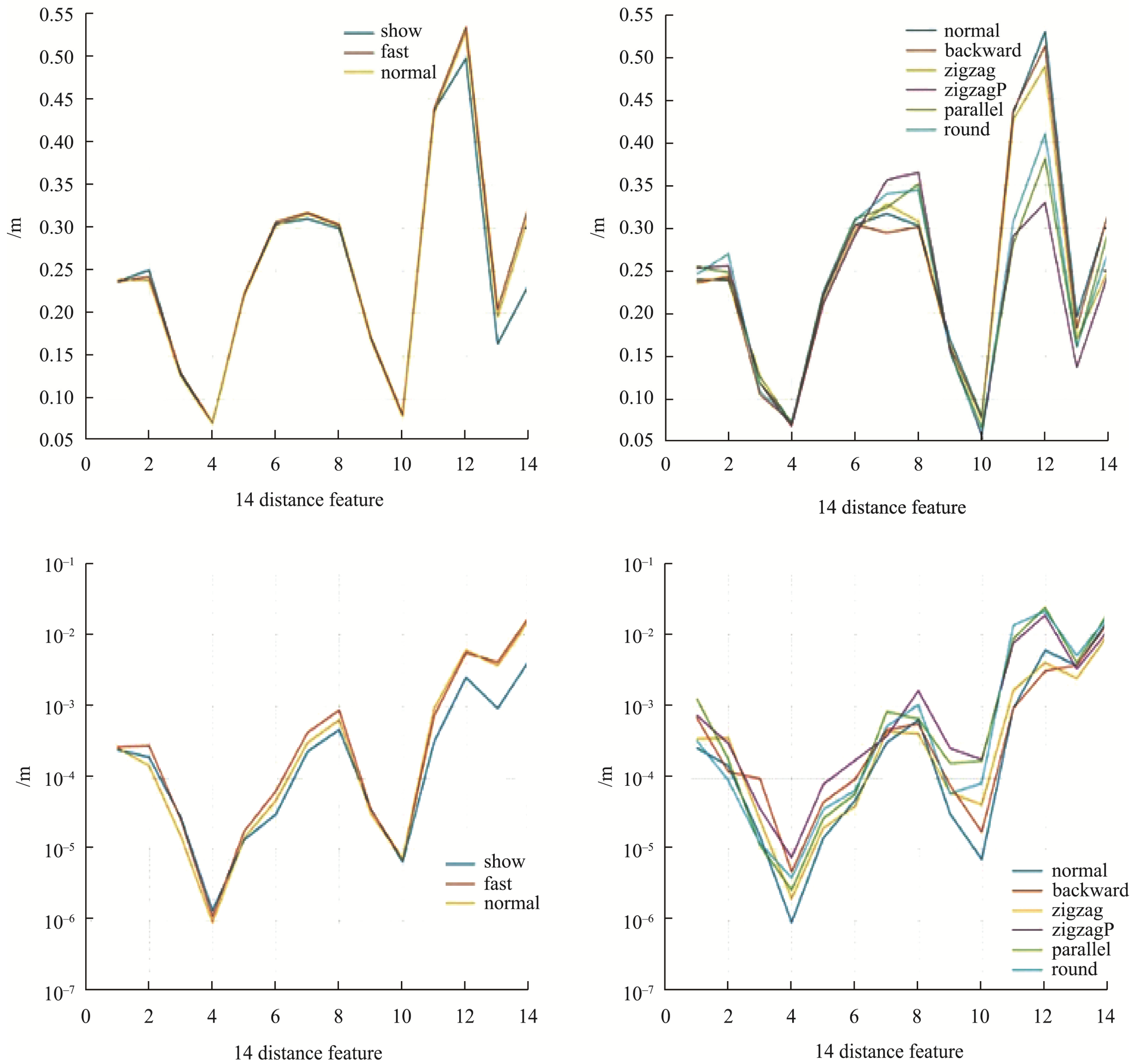

Fig.9 Comparison of Means and Variance under Different Walking Conditions.

The value of the 7th feature (distance between the joint-pair of HipRight and KneeRight) in the backward scenario is smaller than it is in normal scenario, while values in other kinds of scenarios are higher. As for the 8th feature (distance between KneeRight and AnkleRight), the values are higher in the three types of parallel scenarios (ZigzagP, Parallel, Round). That shows that the direction has a significant impact on some lower limbs features. The reason for this is that when walking sideways, even if we use the side that is not hidden, the overlapping of two legs will make the features unstable. Therefore, the features of lower body are not reliable enough for the gait recognition system with variable walking scenarios.

All abnormal directions cause smaller relative distance features, especially the three sideways directions. This is also caused by the occlusion of the part of the body.

The slow speed will produce a steadier data due to the fact that the variance in the slow scenario is lower. The experimentation further shows that all abnormal directions will cause more noisy data than the normal direction, especially in three sideways directions.

4.3 Improvement of Recognition Rate

There are several reasons which may influence the recognition rate under different conditions. The following section will illustrate how these factors influence the recognition performance.

4.3.1 Selection of Features

After comparing the recognition rate with different selections of features in Table 6, we can find that the performance is improved by adding relative distances and their variances. Also, the recognition rate of zigzag, slow, and normal scenarios are higher when variances of distances are considered. However, if the subject walks at a fast speed, the variances should not be included in the distance features as it will reduce the recognition accuracy. Furthermore, the more angle features will lead to a more accurate gait recognition.

Table 6 Feature Selection

Number of Distance Features	Feature Selection
8	F_r, F_{rv}
14	F_l, F_r
20	F_l, F_{lv}
28	F_l, F_{lv} ,F_r, F_{rv}

4.3.2 Feature Fusion

Additionally, the effects of the feature fusion methods: score-based fusion and rank-based fusion, are compared. In most cases except for normal and zigzag, the recognition rate of score-based fusion is much better than rank-based fusion with 10%-20%. In the normal scenario, the difference is only 2.5%. So a conclusion can be drawn that the score-based fusion method should be applied in real life for a better performance in various walking scenarios.

5 Conclusions and Future Work

This paper extracts three kinds of features to realize gait recognition, as well as conducts one of the first studies to evaluate the effect of different speed and walking direction conditions on the gait recognition performance. The results of this study can play an active role in improving the robustness of gait recognition systems under different conditions.

Based on the observations, the best choice for the most accurate gait recognition would be detecting gait cycle with the improved method in forward direction at a normal or slow speed. We observed that varied speed has a less significant effect on the performance of recognition than the walking direction. We also observed that the overall gait recognition rate will be improved with the more data available and with the training under diverse scenarios.

Comparing various walking directions, we observe that the sideways walking direction have the most impact on the gait recognition. On the one hand, many factors that affect the Kinect data collection can be avoided by placing the Kinect in such a way that subjects walk directly towards the Kinect sensor. On the other hand, the recognition in various walking directions is still implementable with choosing a proper gait cycle detection method and extracting suitable features as mentioned in this proposed method.

Future work entails a few different avenues for investigation. Study of other factors that may influence the performance of gait recognition, including clothing, accessories, changes in trajectories and walking surfaces can be conducted. The effects of speed and direction conditions on other classification methods may be studied. Finally, we observed that some directions have a significant impact on the recognition rate. Based on this, improvement to gait recognition methods for such specific scenarios can be explored in the future work.

Acknowledgment

The authors would like to acknowledge China Scholarship Council for partial support of this research. Also, heartfelt thanks to Prof. Shao for his help and guidance, as well as China University of Petroleum and all members of the Biometric Technologies lab at the University of Calgary.

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