

# Kinect-Based Gait Recognition Using Sequences of the Most Relevant Joint Relative Angles

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## ABSTRACT

This paper introduces a new 3D skeleton-based gait recognition method for motion captured by a low-cost consumer level camera, namely the Kinect. We propose a new representation of human gait signature based on the spatio-temporal changes in relative angles among different skeletal joints with respect to a reference point. A sequence of joint relative angles (JRA) between two skeletal joints, computed over a complete gait cycle, comprises an intuitive representation of the relative motion patterns of the involved joints. JRA sequences originated from different joint pairs are then evaluated to find the most relevant JRAs for gait description. We also introduce a new dynamic time warping (DTW)-based kernel that takes the collection of the most relevant JRA sequences from the train and test samples and computes a dissimilarity measure. The use of DTW in the proposed kernel makes it robust in respect to variable walking speed and thus eliminates the need of resampling to obtain equal-length feature vectors. The performance of the proposed method was evaluated using a Kinect skeletal gait database. Experimental results show that the proposed method can more effectively represent and recognize human gait, as compared against some other Kinect-based gait recognition methods.

## Keywords

Gait recognition, Kinect v2, joint relative angle (JRA), DTW-kernel, motion analysis.

## 1 INTRODUCTION

Over the past ten years, biometric recognition and authentication has attracted a significant attention due to its potential applicability in social security, surveillance systems, forensics, law enforcement, and access control [1, 2]. A biometric system can be defined as a pattern-recognition system that can recognize individuals based on the characteristics of their physiology or behavior [3, 4]. Gait is one of the very few biometrics that can be recognized at a distance without any direct participation or cooperation of the user. Gait recognition involves identifying a person by analyzing his/her walking pattern. Since human locomotion is a complex and dynamic process that comprises movements of different body limbs and their interactions with the environment [5], disguising one's gait or imitating some other person's gait is quite difficult. As a result, gait recognition is particularly useful in crime scenes where other biometric traits (such as face or fingerprint) might

be obscured intentionally [6]. The non-invasive nature and the ability to recognize individuals at a distance makes gait an attractive biometric modality in security and surveillance systems [7, 8]. In addition, gait analysis has many applications in virtual and augmented reality, 3D human body modeling and animation [9, 10], motion and video retrieval [11], health care [12]), etc.

In this paper, we present a new Kinect-based gait recognition method that exploits the relative motion patterns of different skeletal joints to represent the gait features. The proposed method encodes the relative motion between two joints by computing the joint relative angles (JRA) over a complete gait cycle. Here, JRA is defined as the angles formed by the corresponding two joints with respect to a reference point in a 3D space. Relevance of a particular joint pair in gait feature representation is then evaluated based on an intuitive statistical analysis that reflects the level of engagement of a particular joint pair in human walking. Finally, we introduce a new dynamic time warping (DTW)-based kernel, which is used to compute the dissimilarity between the collection of JRA sequences obtained from two gait samples. The performance of the proposed method is evaluated using a 20-person skeletal gait database captured using the Kinect v2 sensor. The experimental analysis shows that the proposed method can represent and recognize human gait in a more effective manner,

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as compared against some existing Kinect-based gait recognition methods.

## 2 RELATED WORK

Different gait recognition methods found in literature can be divided into two categories: i) model-based approaches and ii) model-free approaches [13]. In model-based approaches, explicit models are used to represent human body parts (legs, arms, etc.) [14]. Parameters of these models are estimated in each frame and the change of the parametric values over time is used to represent gait signature. However, the computational cost involved with model construction, model fitting, and estimating parameter values makes most of the model-based approaches time-consuming and computationally expensive [14]. As a result, they are unsuitable for a wide range of real-world applications. One of the early parametric gait recognition methods was proposed by BenAbdelkader et al. [15], where they estimated two spatiotemporal parameters of gait, namely stride length and cadence as two distinctive biometric traits. Later, Urtasun and Fua [16] proposed a gait analysis method that relies on fitting 3-D temporal motion models to synchronized video sequences. Recovered motion parameters from the models are then used to characterize individual gait signature. A similar approach proposed by Yam et al. [17] models human leg structure and motion in order to discriminate between gait signatures obtained from walking and running. Although this method presents an effective way to view and scale independent gait representation, it is computationally expensive and sensitive to the quality of the gait sequences [18].

Instead of modeling individual body parts, the model-free approaches utilize the silhouette as a whole in order to construct a compact representation of walking motion [14]. Gait energy image (GEI) [19] and motion energy image (MEI) [20] are two of the most well-known model-free gait recognition methods. The basis of the MEI representation is a temporal vector image. Here, each vector point holds a value, which is a function of the motion properties at the corresponding sequence image [20]. On the other hand, GEI accumulates all the silhouette motion sequences in a single image, which preserves the temporal information as well [19]. Many of the recent model-free gait recognition methods extend GEI to a more robust representation. For example, Chen et al. [21] proposed frame difference energy image (FDEI), which utilizes denoising and clustering in order to suppress the influence of silhouette incompleteness. Li and Chen [22] fused foot energy image (FEI) and head energy image (HEI) in order to construct a more informative energy image representation. Although model-free approaches are computationally inexpensive, they are sensitive to

view and scale changes and therefore, not suitable in uncontrolled environments.

While biometric gait recognition has been studied for the past twenty years, the recent popularization and low cost of Kinect has contributed to the spike in the interest in gait recognition using Kinect data. Kinect is a low-cost consumer-level device made up of an array of sensors, which includes i) a color camera, ii) a depth sensor, and iii) a multi-array microphone setup. Figure 1 shows different data streams that can be obtained from the Kinect. In addition, Kinect sensor can track and construct a 3D virtual skeleton from human body in real-time [23] (as shown in Figure 2), which renders the time consuming video processing steps unnecessary. All these functionalities of Kinect have led to its application in different real-world problems, such as home monitoring [24], health care [25], surveillance [26], etc. The low computation real-time skeleton tracking feature has encouraged some recent gait recognition methods that extract features from the tracked skeleton model. One of the pioneer studies conducted by Ball et al. [7] used Kinect for unsupervised clustering of gait samples. Features were extracted only from the lower body part. Preis et al. [27] presented a Kinect skeleton-based gait recognition method based on 13 biometric features: height, the length of legs, torso, both lower legs, both thighs, both upper arms, both forearms, step-length, and speed. However, these features are mostly static and represent individual body structure, while gait is considered to be a behavioral biometric, which is more related to the movement patterns of body parts during locomotion. Gabel et al. [28] used the difference in position of these skeleton points between consecutive frames as their feature. However, the proposed method was only evaluated for gait parameter extraction rather than person identification.

In this paper, we investigate Kinect-based gait recognition by the means of a new feature, namely the joint relative angle (JRA). The motivation is to capture the relative motion patterns of different joint pairs by examining how the corresponding relative angle between them varies over time. We also introduce an extension of the dynamic time warping (DTW) method, namely the DTW-based kernel that evaluates a collection of JRA sequences for the recognition task.

## 3 PROPOSED METHOD

The proposed new gait recognition method utilizes the 3D skeleton data obtained from the Kinect v2 sensor. Robustness to view and pose changes are the main advantages offered by the proposed method. Released in mid-July 2014, Kinect v2 offers a greater overall precision, responsiveness, and intuitive capabilities than the previous version [29]. The v2 sensor has a higher depth fidelity that enables it to see smaller objects more

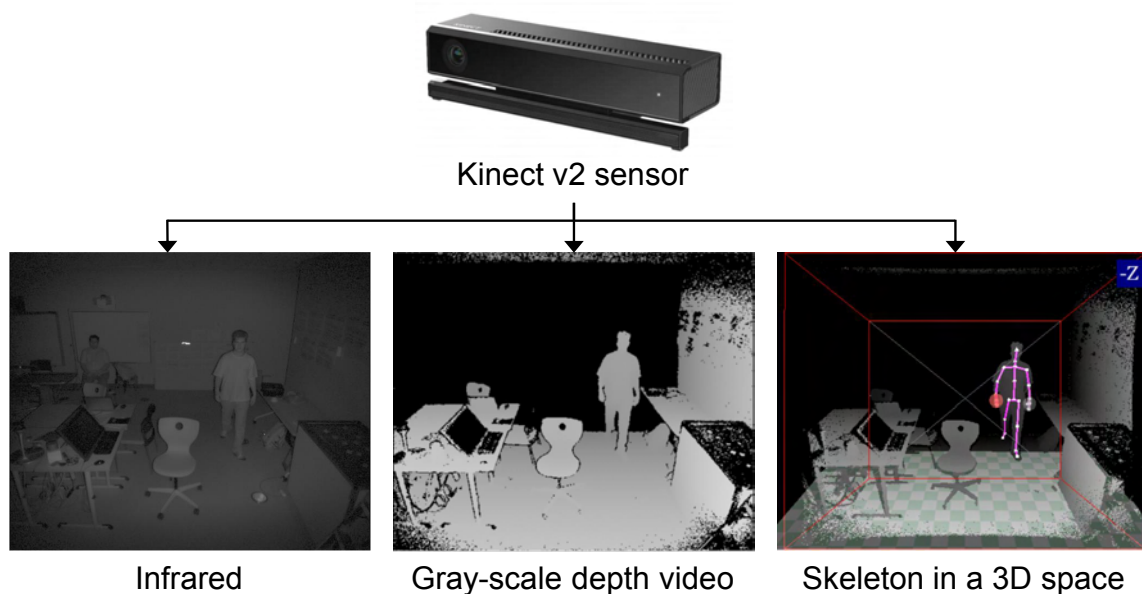


Figure 1: Different data streams obtained from the Kinect v2 sensor.

clearly, which results in a more accurate 3D object construction [29]. It can track a total of six people and 25 skeletal joints per person simultaneously [29]. In addition, while the skeleton tracking range is broader, the tracked joints are more accurate and stable than the previous version of the Kinect [29].

There are several steps involved in the proposed gait recognition method. The first step is to detect a complete gait cycle from the video sequence captured using the Kinect sensor. Since gait is a cyclic motion, detection of a complete gait cycle facilitates consistent feature extraction. Next, joint relative angle (JRA) features for different joint-pairs are computed over the complete gait cycle. One of the main advantages of using angle-based feature representation is that it is scale and view invariant. As a result, recognition is not constrained by a fixed distance from the camera or individuals walking only towards a specific direction in front of the camera. In order to assess the relevance of a particular JRA feature in gait representation, we employ a statistical analysis that evaluates the corresponding joint pair based on their involvement in gait movement. Only the most relevant joint pairs are considered in the proposed JRA-based gait feature representation. Once the feature representation is obtained, the proposed dynamic time warping (DTW)-based kernel is used for the classification task. The proposed kernel takes a collection of the most relevant JRA sequences from both the training and test samples as parameters and computes a dissimilarity measure between them. One particular advantage of the proposed kernel is that, it can match variable length JRA sequences originated due to variable walking speed in different videos of the same person,

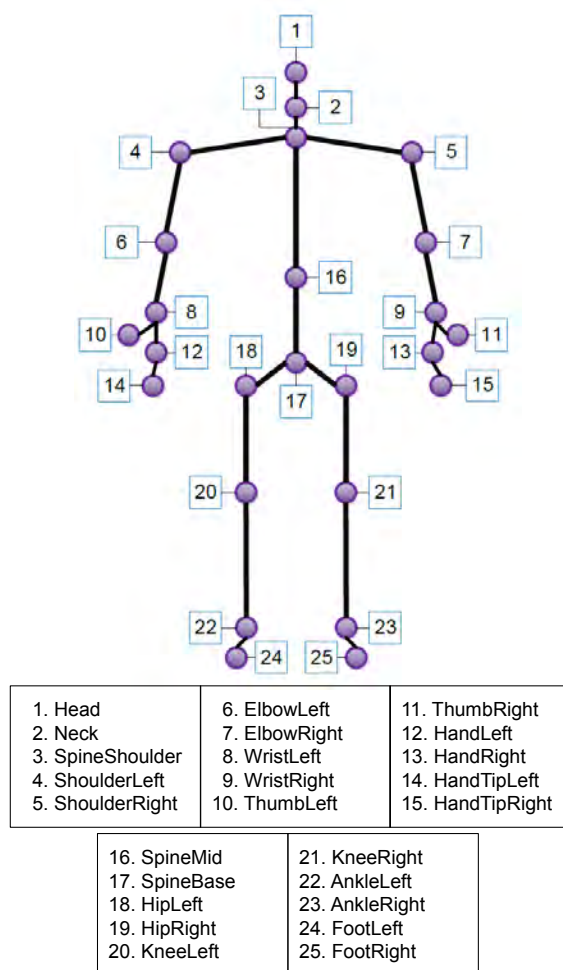


Figure 2: 3D skeleton joints tracked by the Kinect v2 sensor.

thus eliminating any need of pre-processing steps, such as resampling. Figure 3 shows the overview of the proposed gait recognition method.

### 3.1 Gait cycle detection

The first task of any gait recognition method is to isolate a complete gait cycle so that salient features can be extracted from it. Regular human walking is considered to be a cyclic motion, which repeats in a relatively stable frequency [14]. Therefore, features extracted from a single gait cycle can represent the complete gait signature. A gait cycle is composed of a complete cycle from rest (standing) position-to-right foot forward-to-rest-to-left foot forward-to rest or vice versa (left foot forward followed by a right foot forward) [30]. In order to identify gait cycles, the horizontal distance between the AnkleLeft and AnkleRight joints was tracked over time, as shown in Figure 4. A moving average filter was used to smooth the distance vector. During the walking motion, the distance between the two ankle joints will be the maximum when the right and the left leg are farthest apart and will be the minimum when the legs are in the rest (standing) position. Therefore, by detecting three subsequent minima, it is possible to find the three subsequent occurrences of the two legs in the rest position, which corresponds to the beginning, middle, and ending points of a complete gait cycle, respectively [31].

### 3.2 Gait feature representation using joint relative angle (JRA)

The skeleton constructed by the Kinect v2 sensor comprises a hierarchy of 25 skeletal joints, where a connection between two joints forms a limb. Therefore, the raw data provided by the Kinect for gait is time series of 3D positions of these joints. However, this data lacks properties like invariance against view and scale changes, which makes direct use of this data as features infeasible. We present a new gait feature representation that processes this raw data and extracts the joint relative angles (JRA) formed by different pairs of joints with respect to a reference point. JRA between two joints  $p_1$  and  $p_2$  can be defined as the angle formed by  $p_1$  and  $p_2$  with respect to a reference point  $r$ . Given the coordinates of 3 points  $p_1$ ,  $p_2$ , and  $r$  in a 3-D space, the angle  $\Theta_{p_1, p_2}$  formed by  $p_1 \rightarrow r \rightarrow p_2$  using the right hand rule from  $r$  can be calculated as:

$$\Theta_{p_1, p_2} = \cos^{-1} \frac{\overrightarrow{p_1 r} \cdot \overrightarrow{r p_2}}{\|\overrightarrow{p_1 r}\| \|\overrightarrow{r p_2}\|} \quad (1)$$

Here,  $\overrightarrow{p_1 r} = r - p_1$ ,  $\overrightarrow{r p_2} = p_2 - r$ , the dot(.) represents dot product between two vectors, and  $\|\overrightarrow{p_1 r}\|$  and  $\|\overrightarrow{r p_2}\|$  represent the length of  $\overrightarrow{p_1 r}$  and  $\overrightarrow{r p_2}$ , respectively. The SPINE\_BASE joint was selected as the reference point, since it remains almost stationary during walking.

JRAs computed over time provide an intuitive representation of the relative movements of the joints involved. The advantages of using joint relative angle features are two-fold: firstly, the computed JRA features are view and scale independent. This means that, the feature values will not be affected by the variation of the distance of the subject from the camera or the direction of the subject's walking. Secondly, according to [7], joint distance-based features proposed in recent works [27], [28] are found to vary over time significantly. As a result, consistent feature extraction is difficult in some cases. On the other hand, although the distances of the joints vary over time, angles formed by the joints remain unaffected.

In this study, we consider JRAs originated from a particular joint-pair as a small fragment of a person's gait signature, where the full gait signature is defined as a collection of JRA sequences originated from different joint-pair combinations over a complete gait cycle. For the 25 skeletal joints, there is a total of 300 possible joint-pair combinations, which is a high-dimensional feature space. In addition, not all joint-pair is relevant in gait feature representation. For example, JRAs between the SpineShoulder and the SpineMid joints does not represent any information related to human gait, since both these joints remain almost stationary when a person walks. Therefore, identifying the skeletal joint-pairs that are relevant to human gait motion is imperative for the proposed gait recognition method.

### 3.3 Selection of the most relevant JRA sequences

Since not all skeletal joints engage during human locomotion, not all JRA features are relevant in gait representation. Relevance of a JRA sequence originated from a particular joint pair can be evaluated intuitively by analyzing human walking. In this paper, we present a statistics-based relevant joint pair selection approach, that utilizes histogram of JRA features to evaluate the level of engagement of the corresponding joint pair.

For joint pairs that has high relative motion during gait, the joint relative angles computed over the full gait cycle should have high temporal changes. On the other hand, joint pairs that remains stationary or moves little during gait should have little variation of JRA over the full gait cycle. This can also be represented using histogram of JRA values. For a particular joint pair that has high relative motion during gait, the histogram should have a wide distribution. On the other hand, for joint pairs that has little relative movement, the JRA values will occupy only a few number of bins in the histogram. Figure 5 shows histogram of JRA values computed for different joint pair combinations for 4 different participants. It can be observed that, for some joint pairs ({SpineShoulder, SpineMid},

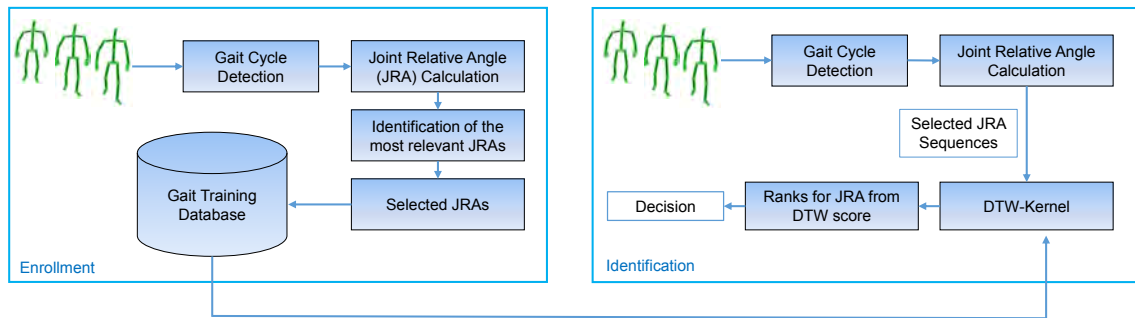


Figure 3: Overview of the proposed gait recognition method.

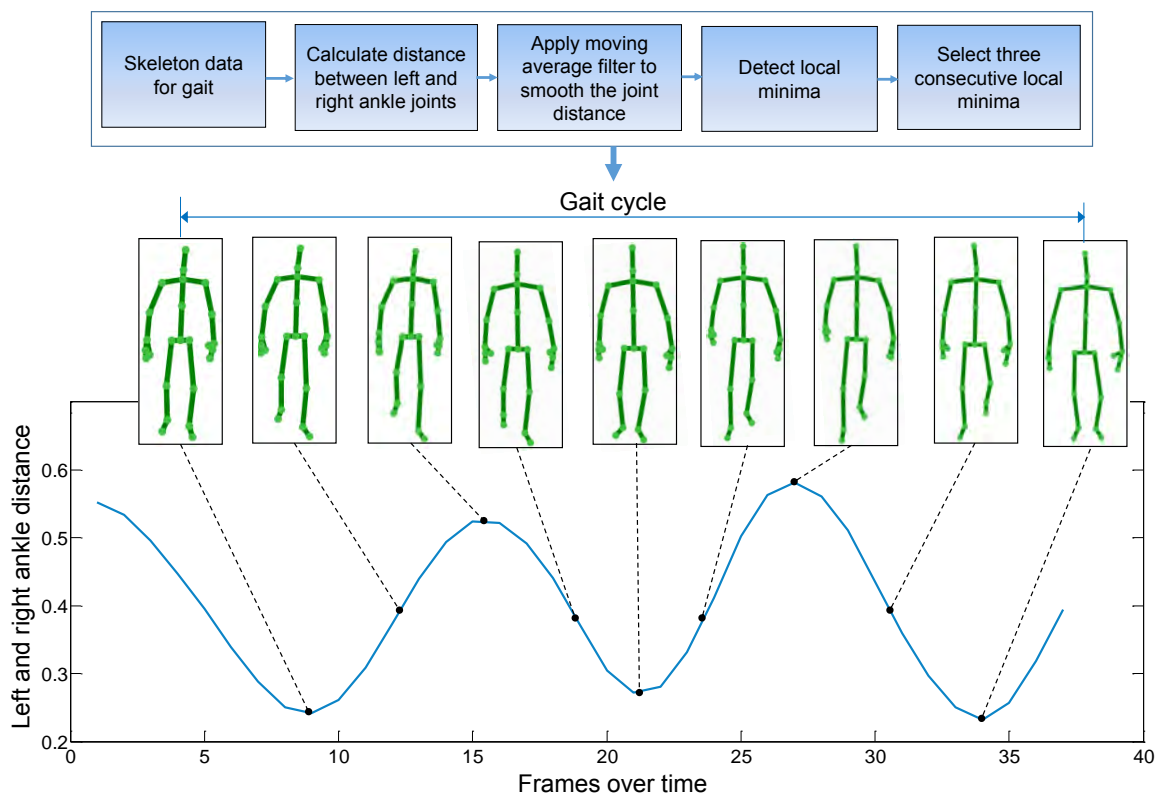


Figure 4: Detection of a complete gait cycle by tracking the distance between the left and right ankle joints.

{ShoulderLeft, ShoulderRight}, {HipLeft, HipRight}), the temporal change of JRA values over the complete gait cycle is really small and therefore, the distribution of JRA values in the histogram is really narrow (occupying only 2 or 3 bins). On the other hand, for joint pairs like {AnkleLeft, AnkleRight}, {ShoulderLeft, AnkleLeft}, and {ShoulderRight, AnkleRight}, the JRA values occupy a large number of bins in the histogram. Based on this observation, we argue that, the number of bins occupied in a JRA histogram of a particular joint pair is an important measure to quantify the level of engagement of the corresponding joint pair in human gait. This, in turn, quantizes the relevance of

the corresponding joint pair in the gait movement. In this paper, we use the number of occupied bins in the JRA histogram of a particular joint pair to represent the relevance of that joint pair in gait feature representation. A high number of occupied bins represents a high relevance, while a small number represents a low relevance.

### 3.4 DTW-kernel for gait recognition

Joint relative angles (JRA) for different joint-pairs computed over a full gait cycle essentially represent sequences of time-series data. Alignment of such temporal gait data is a challenging task due to variation of walking speed, which might result in variable length

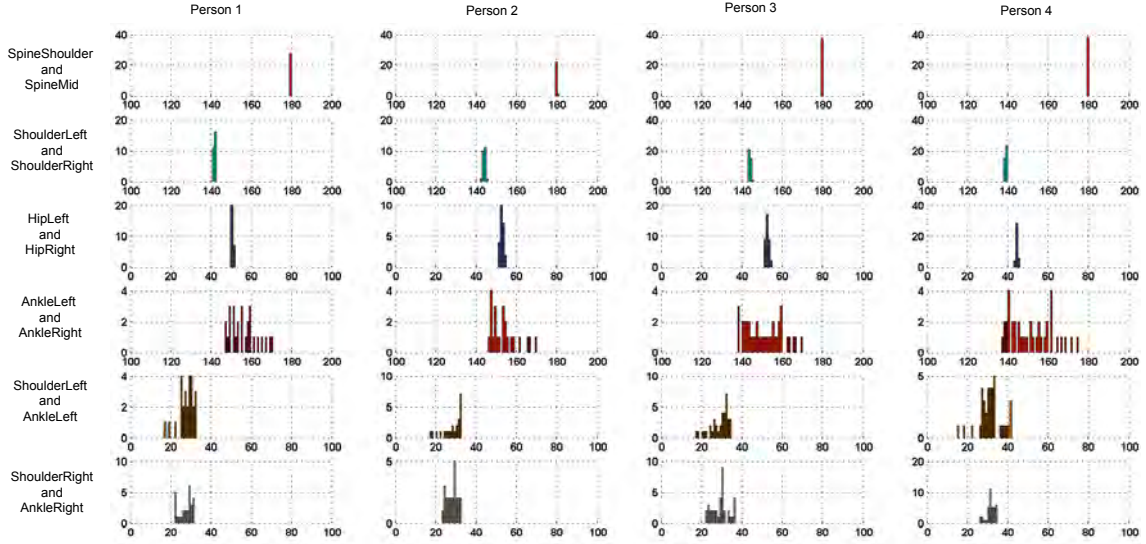


Figure 5: Histogram of JRA values for different joint pairs and persons. It can be observed that, some joint pairs have a wide distribution of JRA values in the histogram, while some other joint pair JRA values occupy only a small portion of the histogram bins.

JRA sequences for the same person. Therefore, applying traditional classifiers in this scenario requires extra pre-processing steps, such as resampling to obtain equal-length feature vectors. However, resampling of time-sequence data involves deletion or adding new data, which might affect the recognition performance. On the other hand, non-linear time sequence alignment techniques can effectively reduce the effect of variable walking speed by warping the time axis. Dynamic time warping (DTW) is a well-known non-linear sequence alignment technique. Originally proposed for speech signal alignment [32], recent DTW applications are mostly verification-oriented, such as offline signature verification [33]. In this paper, we propose to utilize DTW to design a kernel for gait recognition that takes a collection of JRA time series data originated from different joint pairs as the parameter and outputs the dissimilarity measure between two given gait samples. Use of DTW allows the alignment of different length JRA sequences, which enables to match gait samples without any intermediate resampling stage.

Given the set of all joint relative angles  $JRA = \{\theta_1, \theta_2, \dots, \theta_q\}$ , where each  $\theta_i$  represents JRAs for two particular joints with respect to the reference point computed over a full gait cycle, we first obtain a subset of the most relevant JRA sequences:

$$\theta = \{\theta_i | i = 1, 2, \dots, M \text{ where } \theta_i \in JRA\} \quad (2)$$

Let,  $\theta_{train}$  and  $\theta_{test}$  are two JRA sequences from the same joint-pair computed over a complete gait cycle, where the length of  $\theta_{train}$  and  $\theta_{test}$  are represented as  $|\theta_{train}|$  and  $|\theta_{test}|$ , respectively.

$$\theta_{train} = a_1, a_2, a_3, \dots, a_{|\theta_{train}|} \quad (3)$$

$$\theta_{test} = b_1, b_2, b_3, \dots, b_{|\theta_{test}|} \quad (4)$$

Here,  $a_t$  and  $b_t$  are the JRA values of  $\theta_{train}$  and  $\theta_{test}$  at time  $t$ , respectively. Given these two time series, DTW constructs a warp path  $W = w_1, w_2, w_3, \dots, w_L$ , where  $\max(|\theta_{train}|, |\theta_{test}|) \leq L \leq |\theta_{train}| + |\theta_{test}|$ . Here,  $L$  is the length of the warp path between the two JRA sequences. Each element of the path can be represented as  $w_l = (x, y)$ , where  $x$  and  $y$  are two indices from the  $\theta_{train}$  and  $\theta_{test}$ , respectively. There are a number of constraints that DTW must satisfy. Firstly, the warp path must start at  $w_1 = (1, 1)$  and end at  $w_L = (|\theta_{train}|, |\theta_{test}|)$ . This in turn ensures that, every index from the both time series is used in path construction. Secondly, if an index  $i$  from  $\theta_{train}$  is matched with an index  $j$  from  $\theta_{test}$ , it is prohibited to match any index  $> i$  with any index  $< j$  and vice-versa. This restricts the path from going back in time. Given these restrictions, the optimal warp path can be defined as the minimum distance warp path  $dist_{optimal}(W)$ :

$$dist_{optimal}(W) = \min \sum_{l=1}^L \{dist(w_{li}, w_{lj})\} \quad (5)$$

Here,  $w_{li}$  and  $w_{lj}$  are two indices from  $\theta_{train}$  and  $\theta_{test}$ , respectively and  $dist(w_{li}, w_{lj})$  is the Euclidean distance between  $w_{li}$  and  $w_{lj}$ .

We extend this basic DTW formulation to a kernel in order to compute the dissimilarity between a training and a testing gait sample, each of which is a collection of JRA sequences of different joint-pairs. The proposed DTW-kernel aligns the training and testing JRA

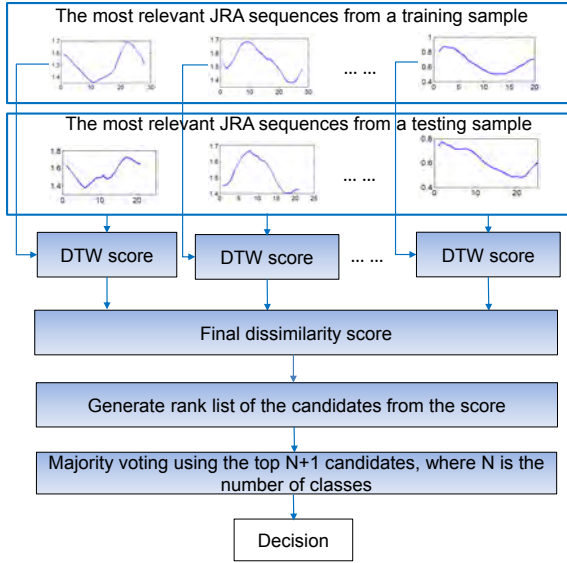


Figure 6: Proposed classification scheme based on the DTW-Kernel and the collection of the most relevant JRA sequences.

sequences of the same joint-pair with each other and computes a match score between them. Summation of all the match scores obtained from the different joint-pair JRA sequences from the training and testing samples is treated as the final dissimilarity measure. Formally, the proposed DTW kernel  $\Delta$  for JRA-based gait representation can be defined as:

$$\Delta(\theta, \theta') = \sum_{m=1}^M \left\{ \min \sum_{l=1}^L \{ \text{dist}(w_{m,li}, w_{m,lj}) \} \right\} \quad (6)$$

Here,  $\theta = \{\theta_1, \theta_2, \dots, \theta_M\}$  and  $\theta' = \{\theta'_1, \theta'_2, \dots, \theta'_M\}$  are collections of JRA sequences from  $M$  different joint-pairs and  $\min \sum_{l=1}^L \{ \text{dist}(w_{m,li}, w_{m,lj}) \}$  represents the minimum warp path distance between the  $m$ -th joint pair JRAs of  $\theta$  and  $\theta'$ .

For the classification task, we first apply the DTW-kernel to compute the dissimilarity score and rank the candidates accordingly. We use this ranklist for a majority voting scheme where the top  $N+1$  ( $N$  is the number of classes) candidates are considered. Figure 6 illustrates the proposed method.

## 4 EXPERIMENTS AND RESULTS

### 4.1 Experimental setup and dataset description

The performance of the proposed method is evaluated using a Kinect skeletal gait database, provided by the SMART Technologies, Calgary, Canada. The gait database comprises 20 participants (14 male, 6

female), from around 20 to 35 years old. For each person, a series of 3 videos was recorded in a meeting room environment. The position of the Kinect was fixed throughout the recording session. Each of the video scenes contains a participant entering the meeting room, walking toward a chair, and then sitting on the chair. Figure 7 shows a frame of a sample video from the gait database. We conducted a 3-fold cross-validation in order to evaluate the effectiveness of the proposed method. In a 3-fold cross-validation, the whole dataset is randomly divided into 3 subsets, where each subset contains an equal number of samples from each category. The classifier is trained on 2 subsets, while the remaining one is used for testing. The average classification rate is calculated after repeating the above process for 3 times. Since the database comprises 3 videos per person, in each fold, two videos were used for the training and the remaining one was used for testing.

### 4.2 Results and Discussions

The first step in our experimental analysis is to detect the most relevant joint pairs in order to represent the gait. For this purpose, we use the methodology proposed in section 3.3. For the 25 skeletal joints tracked by the Kinect v2 sensor, we construct a  $25 \times 25$  matrix for each video sequence, where each cell corresponds to the number of bins occupied in the histogram of JRA values for a particular joint pair. Since our database comprises 20 participants and 3 videos per participant, we obtain a total of 60 matrices. For further analysis, we compute the average matrix from the 60 matrices. A heat map of the obtained  $25 \times 25$  average matrix is shown in Figure 8. The heat map is symmetric on the both side of the diagonal, since the JRA values between joints  $\{J1, J2\}$  and  $\{J2, J1\}$  are same. This map provides a comprehensive representation of the relevance of a particular joint pair in gait representation, where high value corresponds to high relevance and low value corresponds to a low relevance.

Based on this representation of joint pair relevance, we select subsets of JRA sequences for different thresholds and evaluate the recognition performance. For a threshold value of  $t$ , only the joint pair combinations with at least  $t$  bins occupied in the JRA histogram were selected for feature representation. Figure 9 shows the recognition performance of the proposed method for different subsets of JRA sequences selected for different threshold values. It can be observed that, increasing the number of bins excludes some of the less relevant joint pairs in the classification task, thus increasing the recognition performance. The highest recognition rate of 93.3% is obtained for JRA sequences that occupy more than or equal to 20 bins in the corresponding JRA histogram. Increasing the number of selected bins further results in a sharp decrease in the recognition perfor-

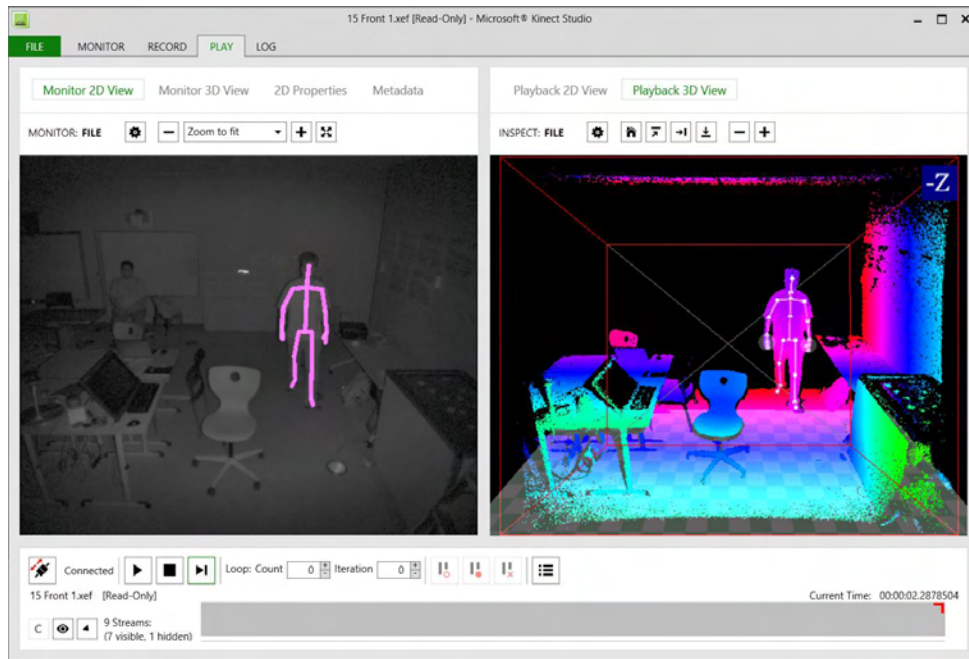


Figure 7: Sample video frame from the gait database captured using Kinect v2 sensor.

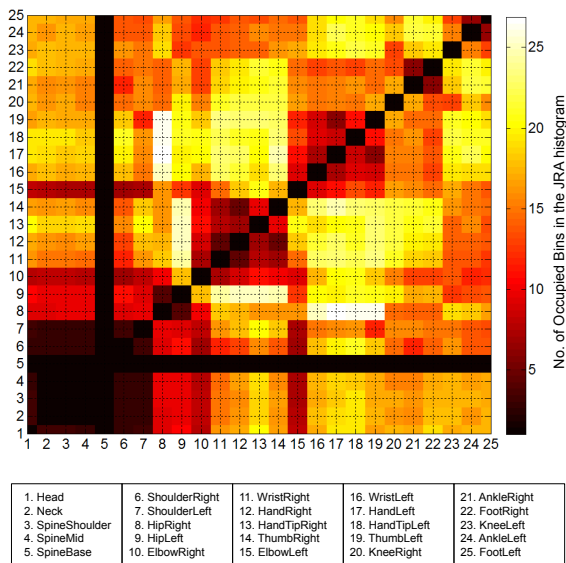


Figure 8: Heat map of the  $25 \times 25$  average matrix obtained for the average number of bins occupied for different JRA histograms for all participants. Here, each point  $(i, j)$  represents the average number of occupied bins in the JRA histogram obtained for joint pair  $\{i, j\}$ .

mance. For the number of occupied bins  $> 20$ , Figure 10 shows a heat map representation of the selected joint pairs. Here, the dark points correspond to the excluded joints, while points with high heat corresponds to a relevant joint pair. This map is also symmetric. Therefore,

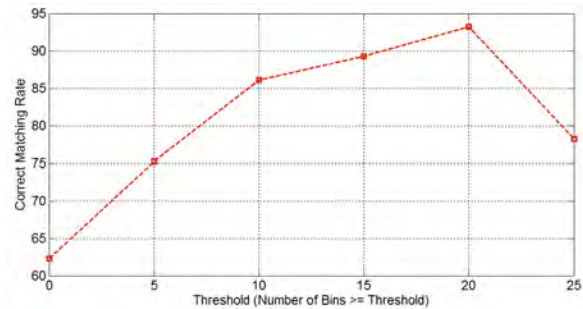


Figure 9: Performance of the most relevant JRA-based gait recognition for different number of occupied bins. The correct matching rate is obtained from 3-fold cross-validation.

only considering upper left triangle or lower right triangle formed by the diagonal (line from  $(1, 1)$  to  $(25, 25)$ ) should be considered.

Finally, we compare the performance of the proposed method against some recent Kinect skeleton-based gait recognition methods. We have selected two studies and tested their performance on our gait database. Details of the selected two methods can be found in [7] and [27]. Table 1 shows the recognition performance of these methods. From the experimental results, it can be said that, gait recognition based on the collection of JRA sequences and DTW-kernel is more robust and achieves higher recognition performance than some of the existing gait recognition methods. The superiority of the proposed method is due to the utilization of view



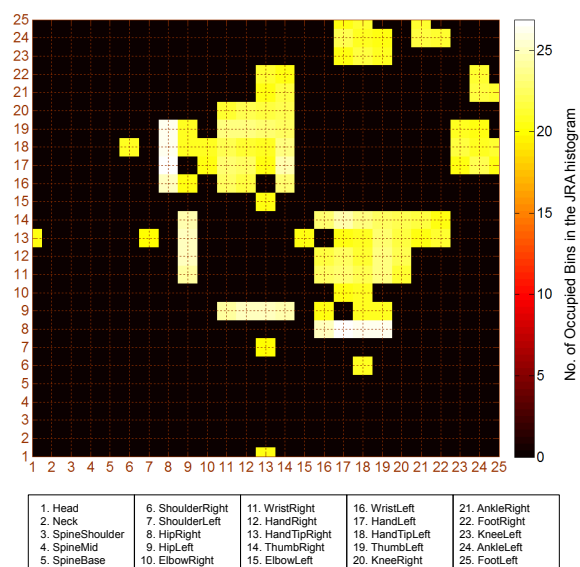


Figure 10: Heat map for the most relevant joint pair combinations found in our experiments. The dark region corresponds to the all joint pair combinations that are excluded from the final feature representation.

and pose invariant relative angle features coupled with a relevance evaluation and non-linear alignment of variable length feature sequences using the DTW-kernel.

Method	Recognition Rate (%)
Collection of the most relevant JRA sequence + DTW-Kernel	93.3
Ball et al. [7]	66.7
Preis et al. [27]	84.2

Table 1: Recognition rates of different methods for 3-fold cross-validation.

## 5 CONCLUSION

This paper presented a new Kinect-based gait recognition method that utilizes the 3D skeleton data in order to compute a robust representation of gait. We introduced a new feature, namely the joint relative angle that encodes the relative motion patterns of different skeletal joint pairs by computing the relative angles between them with respect to a reference point. To evaluate the relevance of a particular JRA sequence in gait feature representation, we constructed histograms of JRA features that can effectively be used to quantize the level of engagement of different joint pairs in human walking. Finally, we propose a dynamic time warping (DTW)-based kernel that takes the collection of the most relevant JRA sequences from both the train and test samples as parameters and computes a dissimilarity measure. Here, the use of DTW makes the proposed kernel

robust against variable walking speed and thus eliminates any need of extra pre-processing. Experiments using a Kinect skeletal gait database showed excellent recognition performance for the proposed method, compared against some recent Kinect-based gait recognition methods. In the future, we plan to extend the proposed method for action recognition and motion retrieval.

## 6 ACKNOWLEDGMENTS

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