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Research article

Personal Re-identification Using Incremental Dynamic Time Warping Algorithm and Body Measurement

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Abstract

Identification of unique individuals is being extensively used in security and surveillance. Gait recognition has caught the attention of computer vision researchers. This interest has been stimulated by the development of systems to automatically identify individuals. This paper presents a gait gesture recognition algorithm, using Incremental Dynamic Time Warping (IDTW) with a body measurement technique that identifies personal gait patterns recorded on video via Microsoft's Kinect® 3D depth-sensing camera. We used the height of a person to further clarify the recognition and accurate identification of the individual. The initial results demonstrated 81.25% accuracy with our gait and height recognition algorithm. This recognition technique is ideal for high-level security requirements.

Keywords

biometrics;

personal re-identification;

Gait recognition;

IDTW;

Kinect sensor

1. Introduction

Demand for the use of biometric systems for human identification at a predetermined distance has led to a significant increase in the number of applications being developed. Many biometric resources, including the iris, fingerprints, palm prints and hand geometry, have been systematically studied and are already employed in systems that are widely used in the security industry. Standard security systems are no longer restricted to static alarms, physical locks or key-card entry systems, which are familiar to most people. The Internet has provided the ability to significantly extend the use of devices for security purposes, in the home and on the street, using electronic identification and remote identification from CCTV systems and other data-gathering devices.

In the home, there are remote door entry systems, device controls, remotely controlled CCTV cameras, and baby monitors. Devices such as panic alarms and motion sensors that can detect if someone has not moved for some time and therefore may require medical assistance, are examples

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of services available on the Internet. In the public domain, safety and security have been enhanced by advanced warnings of traffic, flood, fire, weather and impending disasters.

Automated personal identification systems, such as personal facial recognition and automated motor vehicle registration number checking, are examples of public security protection systems made available by the Internet. Personal identification for security purposes is an interesting and imperative matter for research in the Internet Netscape. Active and passive personal identification systems are now readily available. An active system analyzes personal, physical and biological data through fingerprint and iris recognition while a passive system analyzes data with facial or voice recognition where the results are based on clear data without noise, visual or aural interference that reduces the detection efficiency.

Gesture recognition is an important part of human-computer communication. Interactive body movement and gesture tracking are the basis of many applications including game playing, human-computer interaction, telepresence, health care and security [1-3]. Gait recognition has received a lot of attention from academics and engineers in the field of computer vision because of its high potential for recognition and verification of human identity. Unlike other biometric recognition systems, gait recognition is non-invasive and can identify individuals over relatively long distances without their participation or even knowledge. Human gait is difficult to alter, hide or imitate, which ensures a high accuracy recognition rate. Specifically, since terrorist activities are now more prevalent in today's world, gait recognition is becoming an important tool in security agencies' arsenal. Person re-identification based on the human gait is considered an effective approach for identification as its use can overcome issues such as shape, color, and scale. Due to the human gait being unique for each individual, gait analysis is a practicable option. However, various constraints can impair the efficacy of a gait identification system.

There were several seminal papers available on gait analysis, including Lee and Grimson [4], who emphasized an orthogonal view of a video silhouette of gait motion as a method that allows the aggregation of features over time under difference recognition patterns. Ekinci and Aykut [5] suggested a nonlinear machine method, the kernel of Principal Component Analysis (PCA), to obtain gait features from silhouettes for very single recognition. Toebes *et al*. [6] analyzed a method attentive to health conditions that identified the risk of falling or lapsing into unconsciousness for patients or elders, with the parameters (Local Dynamic Stability: LDS) of gait able to detect a predictor of fall risk. Thang *et al.* [7] presented two methods for biometric gait detection based on acceleration sensors. To examine the data, they used both time and frequency domains. For evaluating the similarity score in the time domain, Dynamic Time Warping (DTW) was applied, and SVM was used for classification in the frequency domain. The outcomes of their proposed methods were 79.1% for DTW and 92.7% for SVM.

In general, the gait recognition results in these approaches were acquired after the movement or gesture has been detected and completed. This means that if these results are to be available for analysis, they need to be captured, recorded and stored for *post facto* analysis. When analyzing long gestures or gait patterns, lengthy analysis is necessary.

The performance of a gait recognition model in verification and identification mode can be measured using the metrics described for a real-time gait gesture analyzing system that was designed and created as part of this research. These metrics were applied to examine the subject's motions by capturing and recording them using a human motion tracking device called the Kinect® 3D depth-sensing camera. From the recording of the person as they passed the sensor, twenty-five points on the upper and lower part of the body at specified particular areas of the person's skeleton allowed this data to be stored in the database [8, 9]. Each data sequence was compared with the Incremental Dynamic Time Warping (IDTW) algorithm and the results improved by combining the body measurements to attain a high accuracy result to successfully develop an accurate personal re-identification technique.

2. Materials and Methods

This section describes the processes for recording the sample gait patterns to create the skeletal models, and compute the feature vectors, as shown in the block diagram (Figure 1).

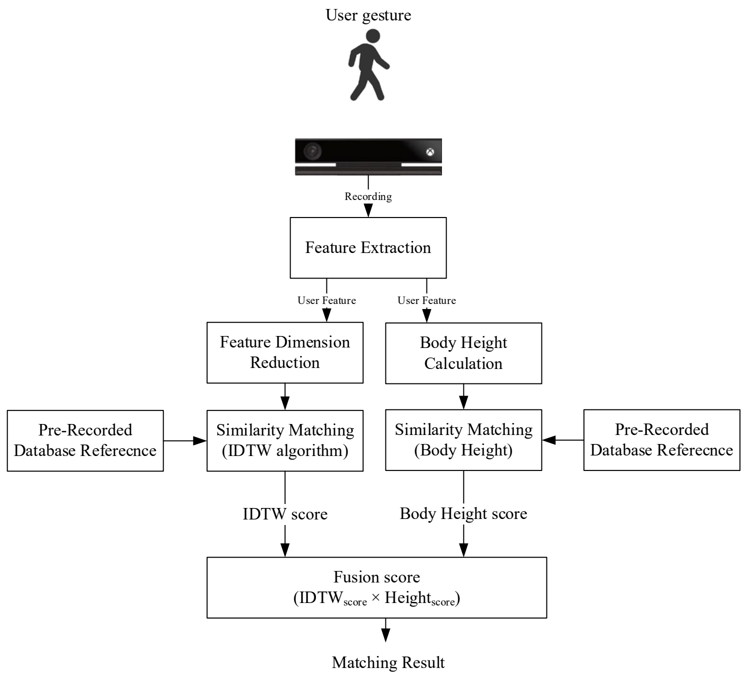

Figure 1. Block diagram

From Figure 1, the first stage in the block diagram is the recording of user gestures from the Kinect® sensor. The system extracts the joint skeleton data of each person who is walking past the sensor and records that data in a database for matching with other recorded data. In the second stage, the data obtained from the sensor is processed to find the similarity by comparing it with the previously recorded data and assessing the estimation into 2 methods. This involves first measuring the similarity of walking posture with the IDTW algorithm and then comparing with body proportion measurements. The results from the comparison are expressed as a similarity score, in which similar sets of data have a point value close to zero. In the third stage, the score obtained from stage 2 is calculated for the new Fusion score using the combined technique of IDTW score and body height score in different proportions to identify results accurately.

2.1 Human gait gesture

Gait is characterized as a facilitated cyclic mix of activities that affects the movement of an individual's body. The movement of the human body presents unique patterns that can identify individuals by the way they walk, as illustrated in Figure 2. There is a sequence of alternative footprints specified in an individual's movement wherein the movement of both feet creates a unique cyclic for each person [10, 11] whether walking, jogging, running, jumping, climbing stairs,

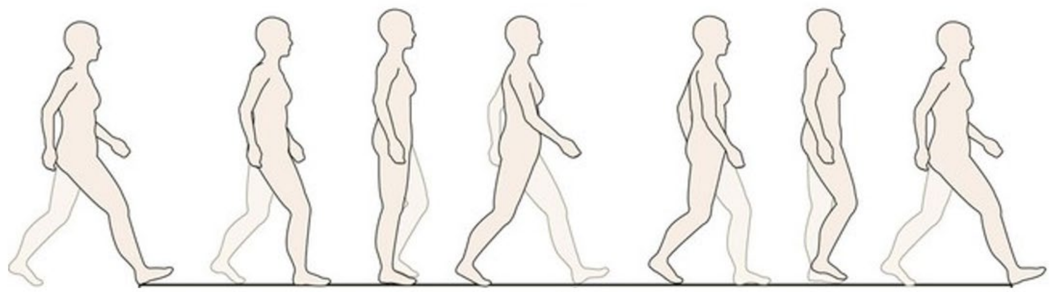

Figure 2. The gait cycle

stretching, relaxing, or bending over. The human gait cycle is split into two separate regions representing the period of time when the foot is in contact with the ground as show in Figure 2.

The gait state can be analyzed as a biometric measurement without contact with the person being scrutinized. This makes it a very versatile method for many purposes. Several researchers have concluded that gait indicates a person's gender and identity [12, 13]. An individual's gait can be detected and measured at low resolution. Therefore, gait can be used in situations where facial or iris data is not available in a high enough resolution for recognition [14].

2.2 Kinect® sensor

The Kinect® sensor is a human motion tracking device for the Xbox 360® console from Microsoft®. It was first intended for use in gaming systems, but many other implementation possibilities have emerged, such as human motion and feature recognition, 3D model reconstruction, robot navigation, medical applications and dance training [15-17].

The Kinect® version 2 has both a 1920x1080 RGB color lens and a 512x424 depth lens with both running at 30 frames per second, with a field of view of 70° horizontal and 60° vertical. In our research, we used the Kinect® sensor API to extract many aspects of the body poses from the depth images, representing a skeletal image with identifiable joints, with twenty-five of them being hierarchically represented, as shown in Figure 3. This camera has the great advantage of being inexpensive and easy to use while providing high accuracy of motion detection in 3D [18, 19].

The human skeleton includes 25 joints with the joint hierarchy flowing from the center of the body to the extremities. Each connection (bone) links the parent joint with a child joint. The Kinect® software attempts to detect the human body image from an overall image that has been taken, and if it can find the body image component, the 3D positions of the 25 joints are estimated. Each joint is represented by a three-dimensional vector (X, Y, and Z) in the coordinate space of the Kinect®. The positions of the joints are written into a text file, frame-by-frame $(x_0, y_0, z_0), (x_1, y_1, z_1), \ldots, (x_{24}, y_{24}, z_{24})$.

From the skeleton representation shown in Figure 2, it can be seen that the middle joint of the hips is applied as the skeletal center joint and the other relative joints are analyzed and calculated from that skeletal center joint. Data retrieved from the Kinect® cannot be used for direct comparison due to the different body joint distances of each person; the joints need to be scaled so that the

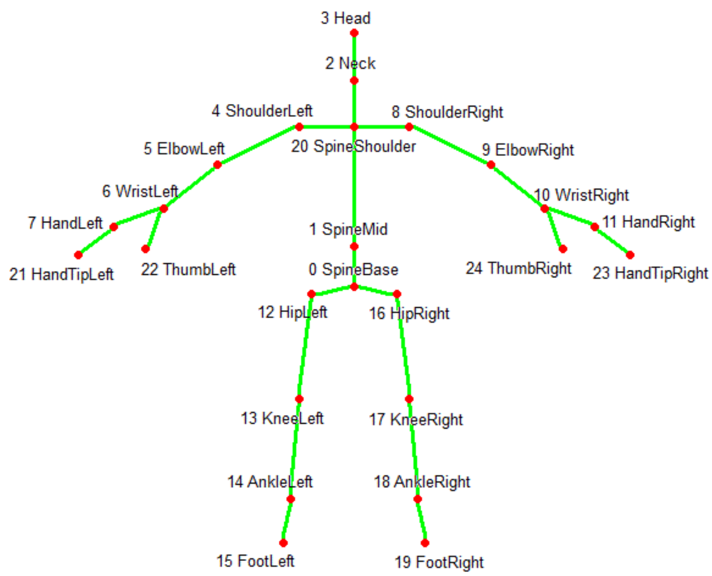

Figure 3. Human skeleton representation captured from the Kinect® sensor

process can accommodate users with different limb ratios [20]. Hence, data normalization is necessary and is done by positioning the spine base as the starting point and measuring each skeleton by spine base position value [15], as shown in equation 1.

$$w_l = \frac{r_l - r_l^0}{\|r_l - r_l^0\|^2}, l = 2, \dots, L \tag{1}$$

where w_l Body joint value at position l
r_l^0 Position value at spine base
r_l Position value at other joint
L The whole number of joints

2.3 Incremental dynamic time warping (IDTW)

IDTW is an algorithm for comparing sequences of different speeds and time intervals by compression or expansion in the time domain and is an extension of the original DTW [21-23]. We used the skeletal feature data of the reference sequence (the stored complete data) as a benchmark and compared it with the new sequence. The algorithm calculates a comparison of the sequences, thereby indicating a degree of sameness between the images, and clarifies distance scores. Figure 4 depicts the time alignment between two independent signals [24], and in our framework, the signals are obtained by the motion-capturing of human walking.

Non-linear alignment provides a more understandable measure of similarity. This allows similar shapes to be matched even if they are out of phase in the time axis. DTW can efficiently find alignment between two sequences, which allows for more complex distance measurement calculations.

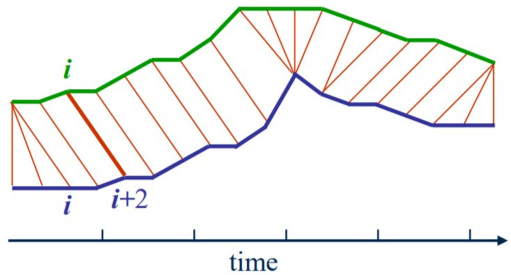

Figure 4. Time alignment of two motion sequences

The original DTW algorithm was defined to match sequences and find an alignment warping path between the two time series $E=\{E_1,E_2,\dots,E_M\}$ and $U=\{U_1,U_2,\dots,U_N\}$ where E is the reference data and U is an unknown. To align these two sequences with the matrix $\boldsymbol{G}_{MxN}$, where the position (i, j) of the matrix contains the distance between E and U, optimal warping was found by minimizing the original DTW distance [21]:

$$D(U,E)=\frac{1}{N}\sum_{t=1}^{T}d(P_t) \tag{2}$$

Here, T is the total number of points on the warping path P and $P_t=(i,j)$ is the t^{th} point on the warping path.

Given the two sequences $E=\{E_1,E_2,\dots,E_M\}$ and $U=\{U_1,U_2,\dots,U_N\}$, the purpose of dynamic time warping (DTW) is to align these two sequences temporally in some optimal sense under certain constraints. The sequence can be a discrete signal, feature sequence, sequence of characters, or any type of time series. Frequently, the index of a sequence relates to successive points in time that are spaced at uniform time intervals. The following Figure 5 shows the alignment between the sequence E of length M=9 and the sequence U of length N=7.

The IDTW algorithm aligns the sequences with the best possible starting reference segment. This can be obtained by ceasing all sequences in every possible frame, calculating the IDTW distance for all frames, and selecting a minimum distance. This can be achieved as follows:

1. The DTW distance is calculated for all $E^j, j=1,\dots,M$, where each E^j is the reference sequence E truncated at the j^{th} frame. i.e., $D(U,E)$, $j=1,\dots,M$
2. The minimum is found using the formula:
$$D_{IDTW}(U,E)=\min_{j=1,\dots,M}D(U,E^i) \tag{3}$$
where $D(U,E^j)$ is defined in equation 2.
3. Steps I and II are iterated for each new sequence. The components of DTW from previous states are reused as the new sequence movement to optimize computation time.

The pseudo-code of the IDTW algorithm is presented in algorithm 1. It can be seen that the next frame in the user sequence is an input to the function. There is only one column added to the cumulative cost matrix G. At that point, this column is filled by reference to a chosen update rule as same as the original DTW. Lastly, the normalized minimum value from the newly added column of the cost matrix G is returned as the current IDTW distance, as shown in Figure 6. It allows the IDTW to calculate the distance score between two sequences faster and with greater accuracy than the classic DTW [9, 25-27].

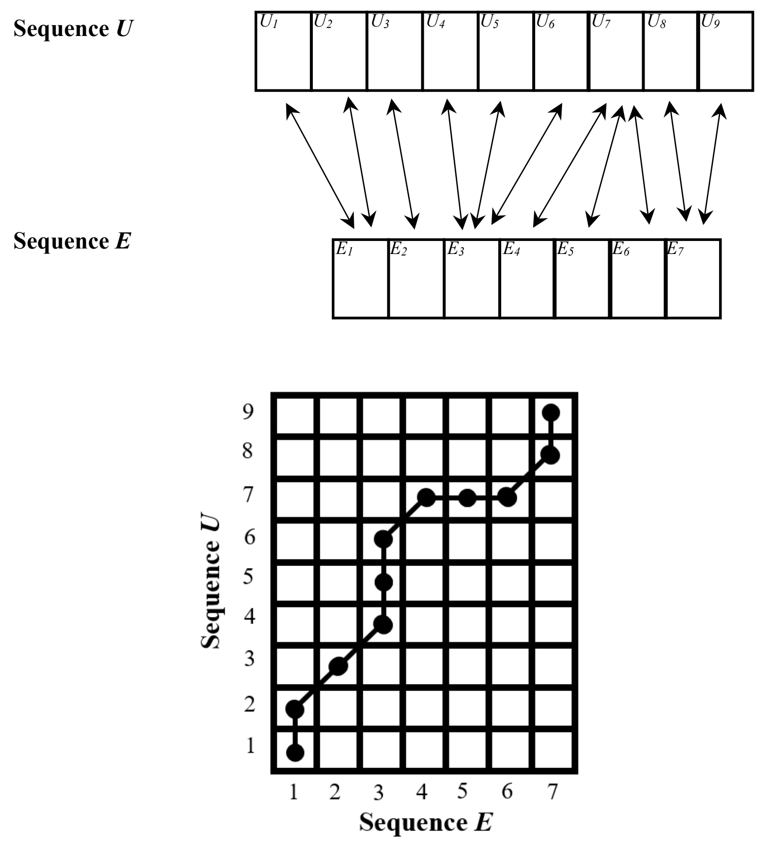

Figure 5. Paths of index pairs for sequence E of length M = 7 and sequence U of length N = 9

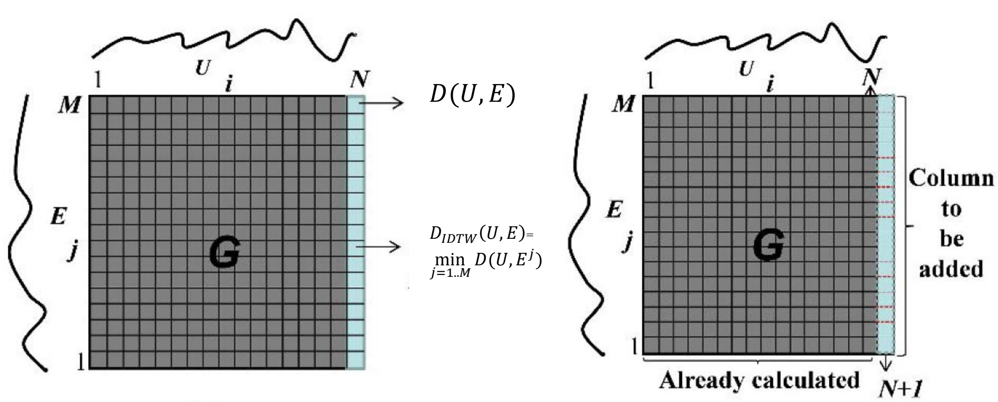

Figure 6. Calculation of final cost: DTW (left matrix) vs. IDTW (right matrix)

Algorithm 1: The IDTW algorithm

Inputs:
U – The unknown sequence up to the current time (length N).
E – The reference (full) sequence (length M).
G – $M \times N$ cumulative cost matrix up to current time.
V – Next frame in user sequence.
Output:
Updated IDTW distance.

```
1:  function IDTW(U,E,G,V)
2:     P ← (N+1)
3:     U_P ← V
4:     G(1…M,P) ← array(1…M)
5:     For i ← (max(1,P),min(M,P)) do
6:        G(i,P) ← min(G(i – 1,P),G(i – 1,P – 1),
           G(i – 1,P – 2)) + D(U_P,Ei)
7:     end for
8:     return min(G(1…M,P))/P
9:  end function
```

2.4 Body height measurement

Kinect® can provide coordinates for the skeleton position, and immediately obtain a three-dimensional image for these points [19, 20]. The joint position property is a set of X, Y, and Z in the 3D space. A number is assigned to each of the joint points relevant to height, so the position of each can be written as $j_i(x, y, z)$ where x and y indicate the position of the joint in the color image, and z indicates the depth position. The distance between x and y is calculated by the Euclidean distance [5], which is defined as equation 4. The formula for estimating the height of a body is presented in algorithm 2.

$$d(x, y) = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \tag{4}$$

For this study, we only used the height of the skeleton backbone (*torso_height*) and right leg (*right_leg_height*) to classify each person, because the leg joint values recorded by the Kinect® sensor cannot be clearly detected while walking. The average height of all frame sequences was used to compute body height.

Algorithm 2: Body Height calculation

Inputs: Kinect body tracking joints.
Output: Body height.

```
1:  height = d(HEAD, NECK) +
             d(NECK, SPINESHOULDER) +
             d(SPINESHOULDER, SPINEMID) +
             d(SPINEMID, SPINEBASE) +
             d(SPINEBASE, avg(HIPRIGHT, HIPLEFT));
2:  left_leg_height = d(HIPLEFT, KNEELEFT) +
             d(KNEELEFT, ANKLELEFT) +
             d(ANKLELEFT, FOOTLEFT);
3:  right_leg_height = d(HIPRIGHT, KNEERIGHT)+
             d(KNEERIGHT, ANKLERIGHT) +
             d(ANKLERIGHT, FOOTRIGHT);
4:  total_height = height + right_leg_height;
```

3. Results and Discussion

This dataset of gait gestures was obtained from 80 individuals by having each person walk past the Kinect® sensor at a distance of two meters (ach person was recorded passing the device twice = 160 sequences). Two meters was the best distance for the angle of camera frame capture [9], as shown in Figure 7. During this experiment, each data sequence was compared to all other recorded sequences with the IDTW, and body height scores, allowing the identification of each individual. The histograms in Figure 8 are graphs that display the distribution of data.

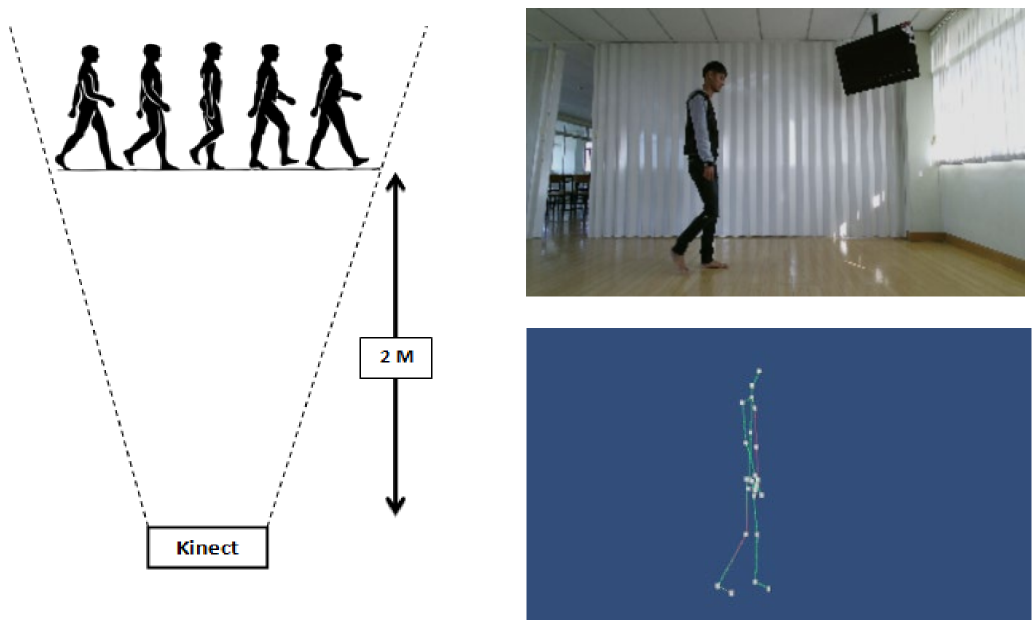

Figure 7. The experimental setting

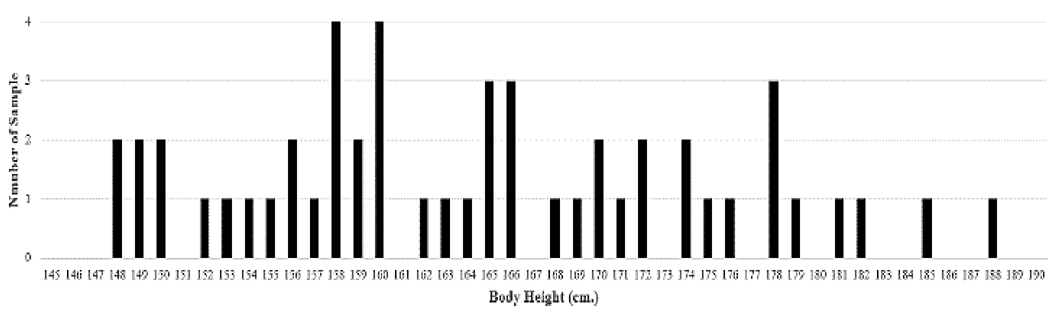

Figure 8. The dataset of 80 body height samples

In the first experiment, each sequence was calculated using the IDTW algorithm. Table 1 contains the distance scores of each gait sequence that indicates the similarity of the gait gesture data patterns. Where the distance score is high, this means that the sequences are different, and where the distance score is close to zero, the sequences are similar, indicating a match and therefore the correct identification of an individual. The recognition accuracy of the IDTW algorithm is 60 out of 80 people at this stage.

The second experiment was to calculate the body height of each of the 80 people. The calculation results were obtained by determining the distance between each person's backbone joints (*torso_height*) and right leg (*right_leg_height*), as shown in Figure 9, calculated by algorithm 2. By comparing each result, each person can be individually identified by their height score (H_{score}) using the following formula:

$$\Delta = |h_1 - h_2| \tag{5}$$

$$H_{score} = \frac{\Delta - Min}{Max - Min} \tag{6}$$

where h_i is body height and Δ is the difference between the body height of each person. If the H_{score} is close to zero then the body heights are almost the same. The accuracy of the comparison results of the height score was 35 out of 80. This demonstrates that the IDTW score can identify people more accurately than the height score.

In the third experiment, we improved the recognition results using a combination of IDTW and height scores in different proportions, which were calculated by the following formula:

$$Fusion_{score} = (\alpha \times IDTW_{score}) + ((1-\alpha) \times H_{score}) \tag{7}$$

where α is the proportion between 0.00 to 1.00. The results shown in Table 1 were calculated by alpha (α) at 0.00, 0.25, 0.50, 0.75 and 1.00 and the accuracies of recognition were 42.50%, 58.75%, and 81.25%, respectively, as shown in a graphical comparison of the accuracy scores in Figure 10.

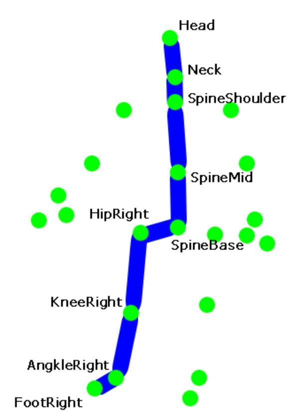

Figure 9. Calculation of body height

Table 1. Result of recognition

Method	Accuracy
IDTW (α=1)	*60 of 80 (75.00%)*
Body Height (α=0)	*35 of 80 (43.75%)*
IDTW×Body Height (α=0.25)	*34 of 80 (42.50%)*
IDTW×Body Height (α=0.50)	*47 of 80 (58.75%)*
IDTW×Body Height (α=0.75)	*65 of 80 (81.25%)*

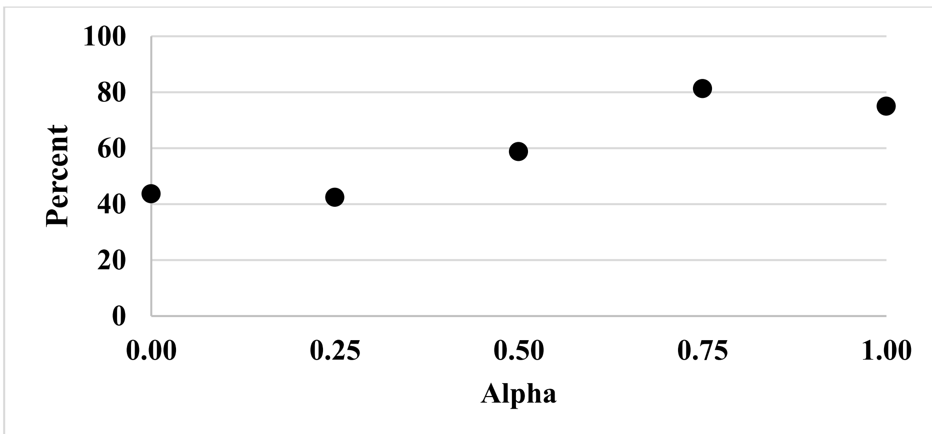

Figure 10. Accuracy of identification

4. Conclusions

In this study, we developed a method for gait gesture recognition by comparing a user sequence to the most closely related reference, which identifies individuals by using a Kinect® camera. The Incremental Dynamic Time Warping (IDTW) algorithm and body height measurements were applied to calculate the similarity between people. To achieve our results, we calculated individual walking motions using IDTW and the individual's body height to classify each person. Our experiments showed a 43.75% accuracy when using a body height measurement technique only since measuring the height of the body while walking can cause the height value to be inaccurate by 1 to 3 cm. As a result, the calculated height classification of each person could decrease overall accuracy. However, the height value can specify the height range of each person when combined with the IDTW algorithm. Using this algorithm, we achieved an 81.25% accuracy which is ideal for high-level security requirements. To quantify accuracy and detect time process for future development, a massive volume of data must be analyzed in real-time. It is acknowledged that we provided a satisfying recognition solution in a relatively ideal environment but did not consider a situation where a person carried a bag or any other item that might hinder data acquisition. Therefore, more relevant algorithms will be investigated in the future.

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