A Framework for Saudi Uniform Gait Recognition Based on Kinect Skeletal Tracking

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Abstract: *Due to its robustness in challenge variation in gait recognition domain, gait recognition is considered as one of the popular remote biometric identification technologies. Gait data may be reliably collected from a long distance and is difficult to conceal or copy. This article investigated the use of Kinect to identify gait in Saudis wearing loose-fitting apparel that conceals the majority of body shapes, such as thobes or abayas. Because these clothes cover the majority of the joints, it is difficult to determine gait. This research uses the Kinect sensor version 2 as a technique to choose the top three joints with the greatest identification results, which are then used for gait recognition. The Y coordinates of joints are used as features, which are then put into the K Nearest Neighbor classification algorithm. Several experiments were carried out, and the results demonstrate that the system has a promising identification rate and is capable of achieving a high recognition performance when identifying or recognizing a person while also dealing with obstacles associated with the types of loose clothing worn by the participants.*

Keywords: *Biometric system, gait recognition, kinect sensor, KNN.*

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1. Introduction

Nowadays, in businesses similar to security, surveillance, healthcare, digital marketing, and gaming, person verification and recognition are hot topics. Face recognition, voice recognition, iris recognition, finger vein recognition, retina recognition, and palm vein recognition are some of the traditional methods that have been utilized for years. Gait analysis is a relatively new addition to the field. This method analyzes a person's walking manner in order to identify or verify the individual. This method is gaining popularity in industries such as medicine and gaming. Regarding human body movement, the Xbox for video games that required human body movement parts without using any remote-control device was first released by Microsoft. Basically, this sensor detects the body's various motions and responds by executing game tasks. Mainly, there are three sensors included in this device. These sensors are: the RGB color sensor, the infrared depth sensor, and the microphone array sensor. The depth sensor is the most important sensor in this research paper. It uses infrared technology for various tasks, such as tracking the skeleton's motions, estimating object distances, providing a 3D model of the body, etc., [2]. The Kinect technology's unique characteristics persuaded and inspired the researchers to employ and utilize it in various applications, such as person recognition and anomaly detection in the human body. The advantages of employing gait analysis for person identification or verification over other standard methodologies are summarized below [6, 9, 10]:

Each person has a unique walking style, and gait analysis features can be captured at a distance of 10 meters.

- For gait recognition, low-resolution video camera sequences are sufficient. Low-resolution video camera sequences are sufficient for gait recognition.
- Gait is difficult to imitate because it is nearly impossible to replicate an individual's exact pattern.

In this paper, a novel gait identification approach based on the movement of the body's top three most discriminative joints as acquired by the Kinect sensor is presented first. Section 2 shows the literature review. Section 3 shows the proposed methodology. The findings and discussions are in section 4. The conclusion and future are covered in section 5.

2. Literature Review

Gait recognition is a new technique in computer vision that is being utilized for various tasks, such as person recognition and tracking. The constant interest of researchers has contributed to the development of this technology, which has become extremely reliable among its users. Nixon and Carter [6] describes the gait recognition methodology in great detail. For gait recognition, Ding *et al*. [4] extracted static features such as bone length and distance between different bones, as well as dynamic features such as joint angles. After preprocessing real-time video, various static and dynamic templates were saved in a dataset. To extract static features, the Euclidean distance between joints was calculated. Gait recognition is one of the newer computer vision techniques that is being used for things like person recognition and tracking. The constant interest of researchers has aided in the development of this technology, which has proven to be highly reliable among its users. Nixon and Carter [6] discusses the gait recognition methodology in great detail. Ding *et al*. [4] extracted static features for gait recognition, such as bone length and distance between different bones, as well as dynamic features, such as joint angles. After preprocessing real-time video, several static and dynamic templates were saved in a dataset. Static features were extracted by calculating the Euclidean distance between joints. Static characteristics were found to be more important than dynamic characteristics. Ioannidis *et al*. [5] describes three new feature extraction approaches for gait recognition. Two approaches based on the Radon transform are proposed: the radial integration transform and the circular integration transform, while the third method is based on weighted Krawtchouk moments. When the Krawtchouk moments were applied to the Gait Cycle (GC) database, they produced the best recognition results. In order to improve recognition accuracy, they also chose a feature fusion structure based on a genetic algorithm. An improvement of 1–8% was obtained using all three types of features. Yoo and Park [14] performed general tensor discriminant analysis on tensor data without vectorization. This enhanced the features while also resolving the oversampling issue. Each gait arrangement was divided into gait cycles after the gait period was defined. A single image representing the entire cycle was created by averaging the silhouettes from each gait cycle. These images were then precisely used as classification features using general tensor discriminant analysis. Gabor's characteristics were also combined with general tensor discriminant analysis. The use of Gabor features, general tensor discriminant analysis, and LDA resulted in a maximum average CMS of 60.58%.

3. Proposed Method

Using a Microsoft Kinect sensor version 2, this paper proposes a skeleton-based gait recognition technique for gait recognition and individual identification. Figure 1 illustrates how the sensor detects an individual's joints, even when the body's joints are hidden by clothing. This figure depicts a man dressed in a Thobe, a traditional and loose Saudi man's garment. It looks a lot like the traditional Saudi woman's dress, the abaya. For 25 human skeletal joints, Kinect offers X, Y, and Z coordinate data. The Microsoft Kinect SDK was utilized to record data for these 25 joints at 30 frames per second (fps). The gait recognition technique utilized is divided into two steps:

1. Creating and developing a user database: the gait sequence was recorded using a Microsoft Kinect sensor, and the X, Y, and Z coordinates of 25 joints were saved. A gait sequence is recorded by going from one direction to another in a straight line perpendicular to the camera view.
2. Classification and feature selection have been eliminated since the X coordinate will definitely increase as a person walks in a straight line perpendicular to the camera view. The Z coordinate provides the distance between the person and the camera. The K-Nearest Neighbor (KNN) algorithm was then utilized to identify individuals based on the Y coordinate of moving joints.

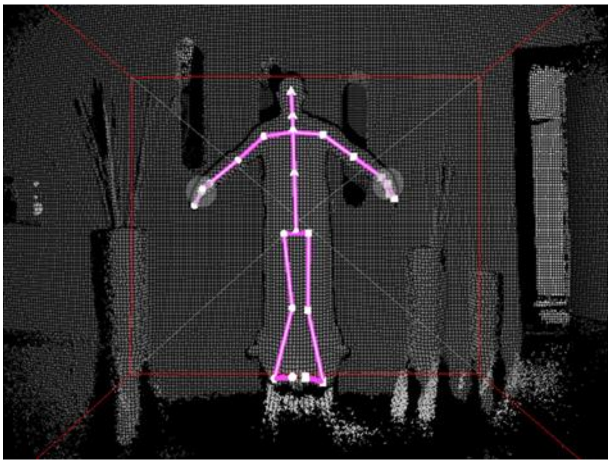


Figure 1. A view of the skeletal tracking by the Kinect sensor.

3.1. Creating Database

The Microsoft Kinect multimodal sensor detects human gait movement and produces non-invasive 3D skeleton photos. The Microsoft Kinect is a relatively inexpensive sensor capable of capturing multimodal sensor data. A database was established for a total of 23 people. Certain joints of the body move in X, Y, and Z coordinates as a person moves. These coordinates can be used to track the walking body's movement. Each joint's X, Y, and Z coordinates vary over time as it moves throughout a person's walk. Figure 2 illustrates a more comprehensive. For each collected frame, the X, Y, and Z coordinates of these joints are kept in a distinct database file. While maintaining the Kinect position fixed, we obtained skeletal data from 25 joints on a person. These files have 25 columns (25 joints), each with a separate joint's X, Y, and Z coordinates. Each row contains the joint coordinates for each collected frame.

The system training GUI is illustrated in Figure 3-a). Each person's data will be entered individually into the database to build user files. Figure 3-b) illustrates how the system is tested using the testing GUI utilizing pre-recorded user data.

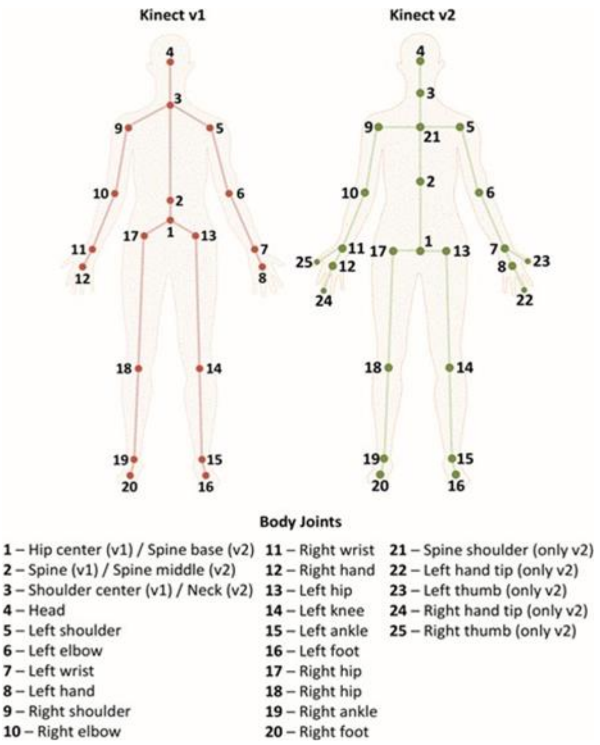
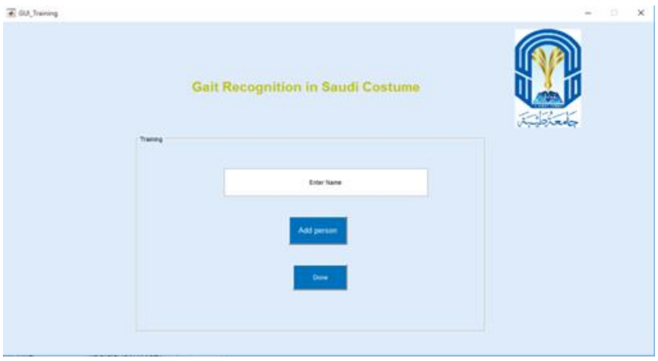


Figure 2. The labelled joints as detected by Kinect [10].



a) Training GUI.

b) Testing GUI.

Figure 3. The GUI utilizing pre-recorded user data training and testing.

3.2. Classification and Feature Selection

Each participant is provided with 35 samples. The data was then separated into training and testing sets. The training set contains around 85% of the whole data, while the testing set contains approximately 15% of the total data. With this distribution of training and testing sets, we can use 30 samples for training and 5 samples for testing. We deleted X and Z coordinate information because: the X coordinate will simply increase in the direction that the person is going, so we know that its value will rise over time—that's not relevant information.

The Z coordinate is also unimportant because it is simply the distance of a joint from the camera. Figure 4 illustrates how the X, Y, and Z coordinates are represented by the Microsoft Kinect.

version 2 sensor.

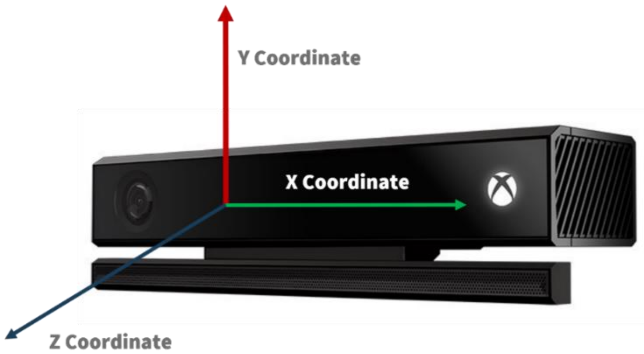


Figure 4. The X, Y, and Z coordinates in the Kinect sensor.

While Y coordinates represent the position of the joint. We have information on 25 joints that move during a person's walk that will be used to classify them. The following steps were considered for each joint ID, ranging from 1 to 25:

a. Use the first 60 frames of the considered joint's Y coordinate sequence (we need a constant number of frames, so we used the first 60 frames). This was because a feature vector was created with the least amount of video data possible (around 60 frames).
b. Each user will have 35 feature vectors because we recorded 35 samples per user. 30 should be set aside for training and the remaining 5 for testing.
c. The KNN is used to determine accuracy with K=11 and applied.

Using the KNN, we'll gain 25 accuracies, with one accuracy number for each joint considered. We can use this information to decide which three joints provide the best accuracy. The remaining joints are then rejected while Thobe and Abaya identify a person in real-time.

4. Results and Discussion

The obtained accuracy for each considered joint is illustrated in Figure 5.

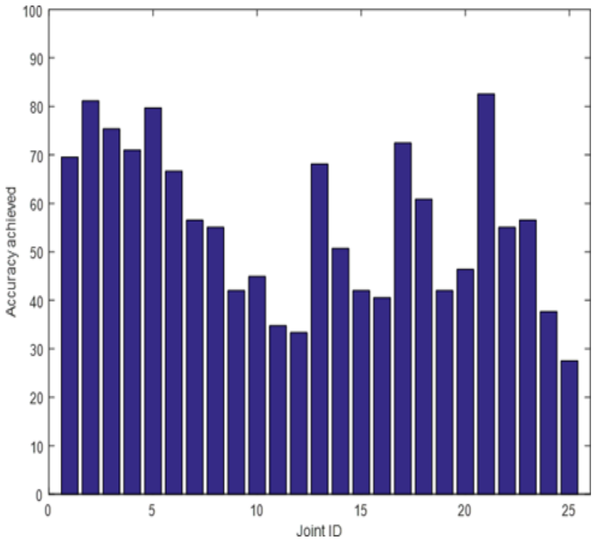


Figure 5. Thea ccuracy per individually considered joint.

Table 1 illustrates the top three joints.

Table 1. The accuracy for each joint separately.

Joint ID	Joint name	Joint accuracy
2	Spine Mid	81.1594%
5	Shoulder Left	79.7101%
21	Spine Shoulder	82.6087%

As a result, these three joints are the most distinct, and their movement pattern can be used to identify a person based on his gait. While these three joints individually provide 81.1594%, 82.6087%, and 79.7101% accuracy, when used together, they provide 92.7536% accuracy for the considered data, as shown and described in greater detail in the confusion matrix in Figures 6 to 9. By observing the correct predictions in the diagonal cells and the incorrect predictions in the remaining cells, we can evaluate the classifier's performance [7, 12, 13].

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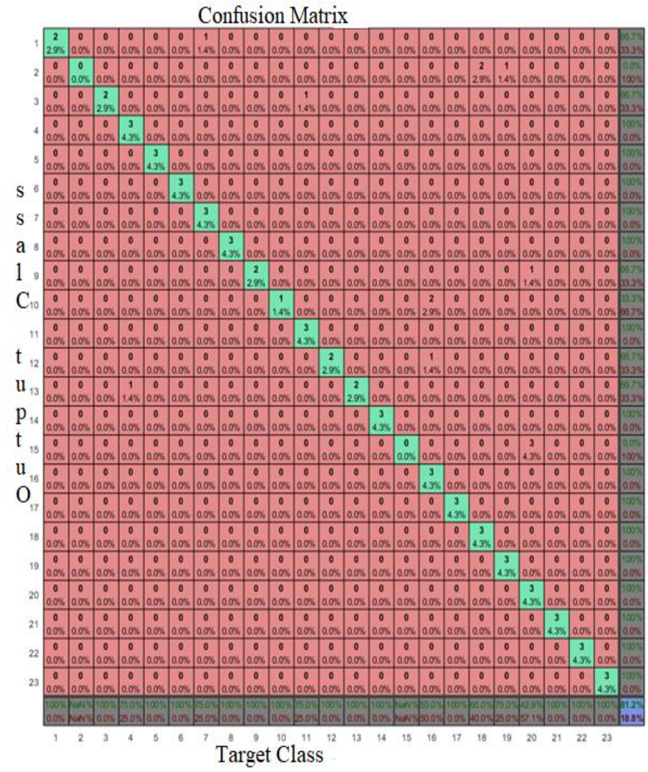

Figure 6. The confusion matrix for Joint 2 with accuracy 81.1594%.

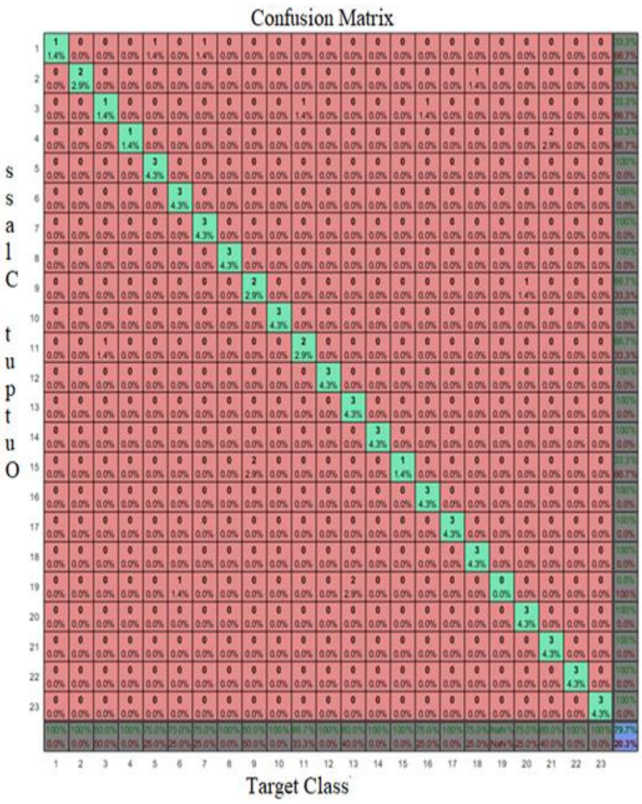

Figure 7. The confusion matrix for joint 5 with accuracy 79.7101%.

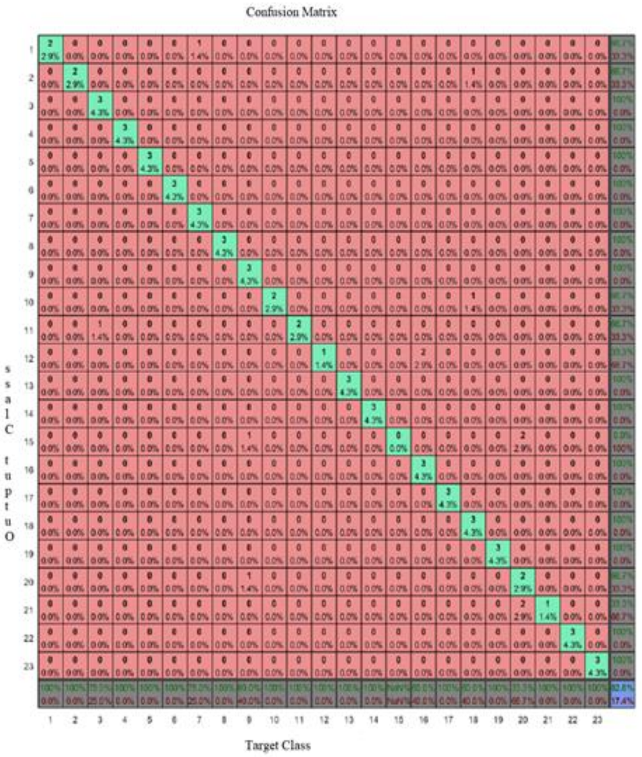

Figure 8. The confusion matrix for Joint 21 with accuracy 82.6087%.

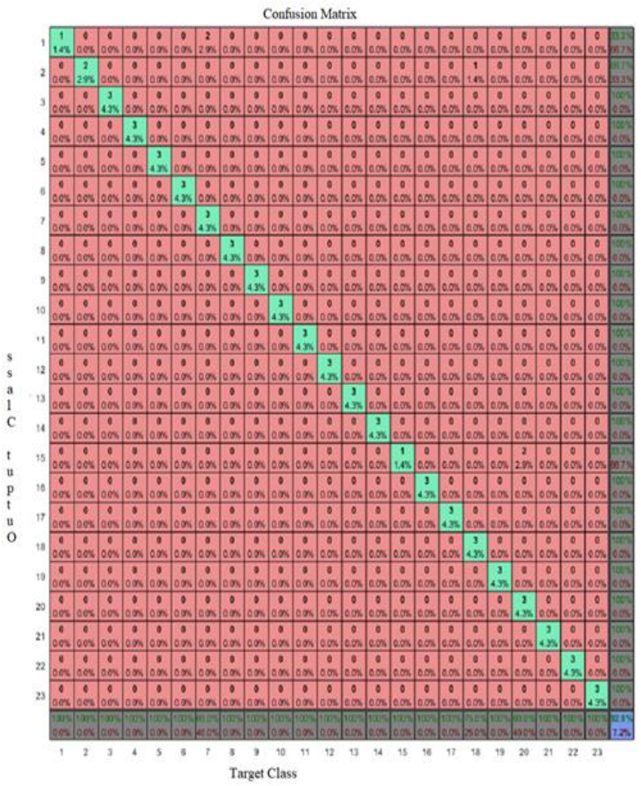

Figure 9. The confusion matrix for combined joints 2, 5 and 21 with accuracy 92.7536%.

As a result, these joints were used in online testing of the algorithm on 23 people in the database. All 35 samples from the database were utilized for training, and each person had online recognition conducted five times. These 23 people each take five online tests, and we can evaluate the accuracy of the classifier's accurate prediction by multiplying the classifier's correct prediction times by the total number of times predicted, as indicated in the equation below.

$$Accuracy = 100 * \frac{105}{115} = 91.3043\% \tag{1}$$

As a result, the classifier's accuracy exceeds 92% and 91% when tested offline and online, respectively. The following evaluation measures [12] were used to assess the results:

a) Accuracy: the percentage of test samples correctly classified across all categories.
b) Sensitivity: the proportion of correctly classified positive samples among all positive samples.
c) Specificity: the percentage of correctly classified negative samples versus the total number of negative samples.
d) Precision: expresses the ratio of the data samples retrieved by our model for a category to the actual data samples present in the data for that category.
e) Recall: a model's ability to find all relevant samples from a set of data.
f) F-score: the best combination of precision and recall, i.e., the harmonic mean of precision and recall
g) When each person was tested online five times, different evaluation measures were produced when each joint was tested separately and also when the three joints were tested together. The evaluation measures for each joint are shown in the following three Tables 2, 3, and 4. And Table 5 shows the assessment measures for all joints combined.

Table 2. Results for Joint 2 (Spine Mid) with accuracy 81.1594%.

Person ID	Sensitivity	Specificity	Precision	Recall	Fscore
1	1	0.98507	0.66667	1	0.8
2	NaN	0.95652	0	NaN	0
3	1	0.98507	0.66667	1	0.8
4	0.75	1	1	0.75	0.85714
5	1	1	1	1	1
6	1	1	1	1	1
7	0.75	1	1	0.75	0.85714
8	1	1	1	1	1
9	1	0.98507	0.66667	1	0.8
10	1	0.97059	0.33333	1	0.5
11	0.75	1	1	0.75	0.85714
12	1	0.98507	0.66667	1	0.8
13	1	0.98507	0.66667	1	0.8
14	1	1	1	1	1
15	NaN	0.95652	0	NaN	0
16	0.5	1	1	0.5	0.66667
17	1	1	1	1	1
18	0.6	1	1	0.6	0.75
19	0.75	1	1	0.75	0.85714
20	0.42857	1	1	0.42857	0.6
21	1	1	1	1	1
22	1	1	1	1	1
23	1	1	1	1	1

Table 3. Results for joint 5 (Left Shoulder) with accuracy 79.7101%.

Person ID	Sensitivity	Specificity	Precision	Recall	Fscore
1	1	0.97059	0.33333	1	0.5
2	1	0.98507	0.66667	1	0.8
3	0.5	0.97015	0.33333	0.5	0.4
4	1	0.97059	0.33333	1	0.5
5	0.75	1	1	0.75	0.85714
6	0.75	1	1	0.75	0.85714
7	0.75	1	1	0.75	0.85714
8	1	1	1	1	1
9	0.5	0.98462	0.66667	0.5	0.57143
10	1	1	1	1	1
11	0.66667	0.98485	0.66667	0.66667	0.66667
12	1	1	1	1	1
13	0.6	1	1	0.6	0.75
14	1	1	1	1	1
15	1	0.97059	0.33333	1	0.5
16	0.75	1	1	0.75	0.85714
17	1	1	1	1	1
18	0.75	1	1	0.75	0.85714
19	NaN	0.95652	0	NaN	0
20	0.75	1	1	0.75	0.85714
21	0.6	1	1	0.6	0.75
22	1	1	1	1	1
23	1	1	1	1	1

Table 4. Results for Joint 21 (Spine Shoulder) with accuracy 82.6087%.

Person ID	Sensitivity	Specificity	Precision	Recall	Fscore
1	1	0.98507	0.66667	1	0.8
2	1	0.98507	0.66667	1	0.8
3	0.75	1	1	0.75	0.85714
4	1	1	1	1	1
5	1	1	1	1	1
6	1	1	1	1	1
7	0.75	1	1	0.75	0.85714
8	1	1	1	1	1
9	0.6	1	1	0.6	0.75
10	1	0.98507	0.66667	1	0.8
11	1	0.98507	0.66667	1	0.8
12	1	0.0.97059	0.33333	1	0.5
13	1	1	1	1	1
14	1	1	1	1	1
15	NaN	0.95652	0	NaN	0
16	0.6	1	1	0.6	0.75
17	1	1	1	1	1
18	0.6	1	1	0.6	0.75
19	1	1	1	1	1
20	0.33333	0.98413	0.66667	0.33333	0.44444
21	1	0.97059	0.33333	1	0.5
22	1	1	1	1	1
23	1	1	1	1	1

Table 5. Results for combined joints 2, 5 and 21 with accuracy 92.7536%.

Person ID	Sensitivity	Specificity	Precision	Recall	Fscore
1	1	0.97059	0.33333	1	0.5
2	1	0.98507	0.66667	1	0.8
3	1	1	1	1	1
4	1	1	1	1	1
5	1	1	1	1	1
6	1	1	1	1	1
7	0.6	1	1	0.6	0.75
8	1	1	1	1	1
9	1	1	1	1	1
10	1	1	1	1	1
11	1	1	1	1	1
12	1	1	1	1	1
13	1	1	1	1	1
14	1	1	1	1	1
15	1	0.97059	0.33333	1	0.5
16	1	1	1	1	1
17	1	1	1	1	1
18	0.75	1	1	0.75	0.85714
19	1	1	1	1	1
20	0.6	1	1	0.6	0.75
21	1	1	1	1	1
22	1	1	1	1	1
23	1	1	1	1	1

This study looked into a novel gait recognition method. As features for a motion path, we used the Y coordinates of three joints from a 3D skeleton. These three joints have the most discriminative features, which were discovered by comparing individual accuracy per independent joint. The joints with the highest accuracy were chosen. On database samples, the offline testing yielded 92.75% accuracy. Furthermore, 91.30% accuracy was achieved for online testing. KNN with K=11 was used as the classifier. As a result, this method is robust enough to use only the three best joints for recognition. This is what makes it ideal for recognizing people even when they are fully clothed, such as in a thobe or an abaya. Despite the previous joints' high accuracy, the results are inconsistent and change as the database participants change. This means that altering the number of participants or the number of joints can result in three distinct joints with varying accuracy ratios. This is evident in Table 6, where we varied the number of participants in the database for the same participants. Table 6 shows the new results after we eliminated a group of participants in descending and random order:

Table 6. The accuracy for different number of participants.

No. of participants	Best 3 joints	Accuracy for each joint	Accuracy for best 3 joints
23 (All participants)	(2) Spine mid (21) Spine shoulder (5) Shoulder left	81.1594% 82.6087% 79.7101%	92.7536%
19	(2) Spine mid (21) Spine shoulder (3) Shoulder center	84.2105% 84.2105% 80.7018%	89.4737%
15	(2) Spine mid (3) Shoulder center (5) Shoulder left	77.7778% 77.7778% 77.7778%	86.6667%
11	(5) Shoulder left (18) Right hip (3) Shoulder center	87.8788% 87.8788% 84.8485%	90.9091%
7	(18) Right hip (1) Spine base (4) Head	100% 95.2381% 95.2381%	95.2381%

The confusion matrix for each group is illustrated in detail in Figures 10, 11, 12, and 13 respectively.

Figure 10. Confusion matrix for 7 participants with accuracy 95.2%.

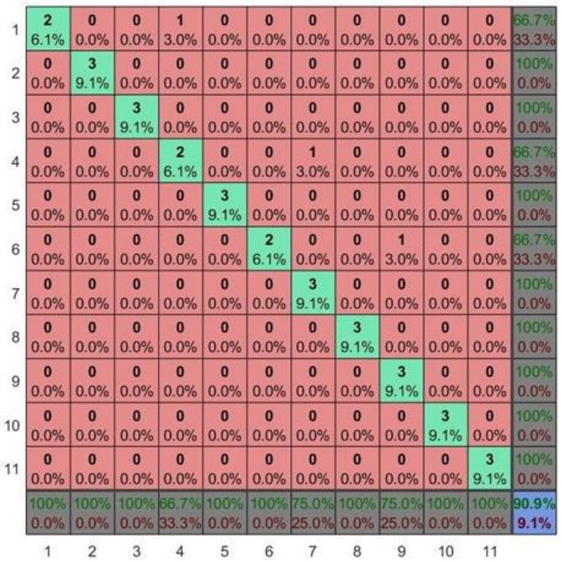

Figure 11. Confusion matrix for 11 participants with accuracy 90.9%.

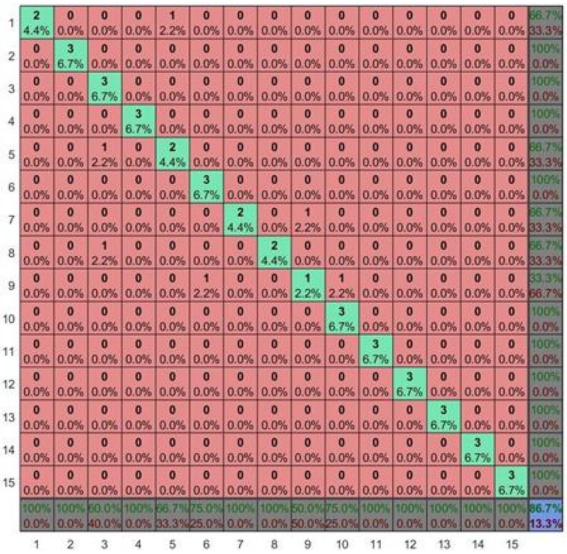

Figure 12. Confusion matrix for 15 participants with accuracy 86.7%.

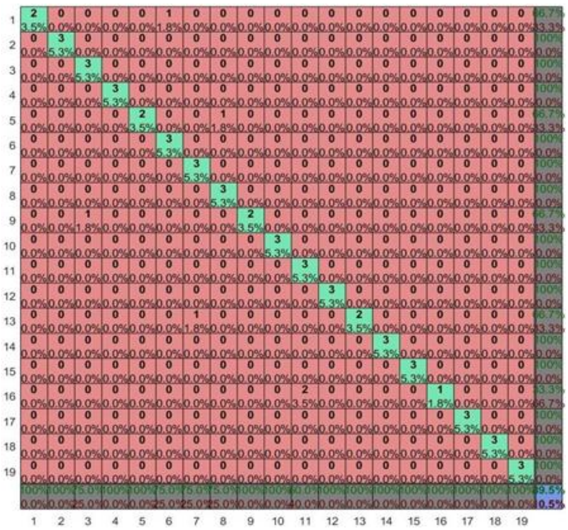

Figure 13. Confusion matrix for 19 participants with accuracy 89.5%.

As a result, the system's output is expected to differ depending on the patterns stored in the database. When the patterns recorded for each person are very similar, high accuracy can be obtained. That is, pattern quality is good when the patterns recorded by each individual are both very similar and distinct from the rest of the patterns recorded by other people in the database, and this will aim to achieve higher accuracy for the system.

5. Conclusions and Future Work

This research paper offers a novel gait analysis method for detecting and recognizing people who are dressed loosely and have the majority of their joints hidden beneath cloth. Individual video feeds were captured using the Kinect sensor. When the three top joints were utilized together, they gave much higher accuracy than any of them did individually—over 92% on the considered data set. A second round of research was also conducted, in which online testing was performed five times for each participant, with an accuracy rate of more than 91%. This indicates the practicality of the proposed method for online person identification. This system can be examined further in the future by placing impediments between the sensor and the individuals. Furthermore, at least 100 subjects from a large database can be tested and validated. Furthermore, multiple people may be visible in real-world scenarios. The algorithm can be expanded in the future to recognize various items.

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