Using Amplitude Modulation for Extracting Gait Features

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Keywords: The Gait Analysis, Spatiotemporal Features, Amplitude Modulation, Classification Technique.

Abstract: Feature extraction for gait analysis has been explored widely over the past years. The set of static and/or dynamic skeleton parameters which are obtained from tracking body joints (i.e. limbs and trunk) are initially pool of gait features extraction. The challenge of gait feature extraction is to reduce the noise in the row data which is due the computational complexity of determination of the gait cycle and sub-phases of the gait cycle, correctly. Although marker-based motion capture systems are highly accurate, they often only used in laboratory environments which leads to a constrained method. Alternative products such as MS Kinect overcome the limitations of the motion capture systems by providing low-cost, moderate accuracy with flexibility of quick installation even in residential settlements. The level of accuracy of the MS Kinect camera for 3D skeleton points can be increased by using pre-processing techniques which helps to overcome the jitter and nose in data. The proposed method modifies the gait walk signal using amplitude modulation (AM) technique to extract high predictive power of gait features without the need of gait cycle determination. Experimental results on 14 health subjects and 3 different types of walking speeds shows that AM technique provides 100% correctly classified instances using support vector machine (SVM) and decision tree (DT) classifiers, while 97.6% with k-nearest neighbour (k-NN) classifier.

1 INTRODUCTION

Human gait analysis is an attractive subject especially for clinical purposes. The vision tracking systems play a main role for tracking and monitoring the 3D skeleton position (Clark et al., 2015). Marker-less MS Kinect provides up to 25 joints position during motion. However, due to the marker-less nature of Kinect cameras cause such systems to suffer from noise. The injected noise can be related to various reasons such as body's parts make itself-occlusion, relative speed of joints to data rate of the Kinect during tracking, etc. This reduces the accuracy of the Kinect outcome as opposed to a marker-based motion capture system. Although the level of accuracy is the main bottleneck for Kinect cameras, they are cost effective and easy to install in residential settlements (Staranowicz et al., 2015).

Recently, human computer interaction that is based on 3D data has been used widely among of researchers (Li et al., 2015). The objective of building 3D skeleton-based human representations is to extract compact, discriminative descriptions to characterise a human's attributes from 3D human skeletal information.

The main goal of this research is to effectively extract gait features from positional lower limbs using the amplitude modulation (AM) technique in order to classify gait speeds. The efficiency of a classifier can be affected by the high predictive power of the classifier, which is related to the success of the feature extraction to define the discrimination between the classes. The human gait analysis is categorised under three groups as gait kinematics, gait kinetics and electromyography (Tao et al., 2012).

This study exploits the spatiotemporal gait analysis which belongs to kinematic measurements for extracting the gait features. The proposed method is based on the 3D skeletal data, which is called modified gait signal using AM. Consequently, the gait features are extracted from the modified gait signal namely, modulation index (D) and baseband frequency of gait signal (fg). The parameters of the modified gait signal are used for classifying the three kinds of walk speeds (slow, normal and fast walk speeds). In classification stage, a comparison between DT, SVM and k-NN classifiers is conducted and efficiency of each classifier is evaluated based on confusion matrix and ROC curve

Elkurdi, A., Caliskanelli, I. and Nefti-Meziani, S.
Using Amplitude Modulation for Extracting Gait Features.
DOI: 10.5220/0006733601610168
In *Proceedings of the 4th International Conference on Information and Communication Technologies for Ageing Well and e-Health (ICT4AWE 2018)*, pages 161-168
ISBN: 978-989-758-299-8

to calculate the accuracy, sensitivity, specificity and area under curve (AUC). The experimental results show that the extracted features using proposed AM method is more efficient than the gait features which are extracted using spatiotemporal gait analysis in walking speed classification.

The rest of this paper is structured as follows. Sec. 2 reviews the related work on spatiotemporal gait analysis and gait features extraction, Sec. 3 covers the proposed amplitude modulation technique for gait features extraction. The experimental setup and results are presented in Sec. 4 and we conclude in Sec. 5.

2 REALTED WORK

2.1 Gait Cycle Determination

Gait cycle is defined as the distance between two consecutive strike heels of the same leg (Tao et al., 2012). The gait cycle composites of two main phases; stance phase and swing phase. Fig.1 illustrates a full gait cycle with a set of sub-stages namely initial contact, loading response, mid stance, terminal stance, pre-swing, initial swing, toe-off, mid swing, terminal swing.

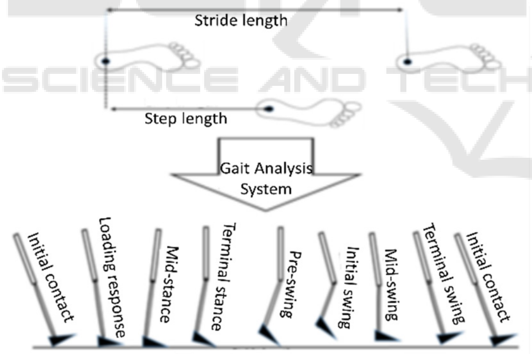


Figure 1: Full gait cycle limited between two strike heels of the same leg.

In (Nguyen et al., 2016) detects the gait cycle from the horizontal distance between the left and right legs during forward walking to the MS Kinect. The author shows exactly that the maximum distances between both legs (which correspond to state of legs) are farthest apart, while minimum horizontal distance between legs are closed to each other. Another study uses a different technique to calculate the full gait cycle is based on spectral signal analysis and detection technique of zero-velocity crossing (Wang et al., 2015).

2.2 Spatiotemporal Gait Parameters

The spatiotemporal gait parameters include gait speed, gait rhythm, stride length, step length, step width, time of single and double support stages and duration of gait cycle (Kim & Son, 2014). Researchers have conducted a wide range of studies on gait parameters by collecting data from lower body limbs. (Clark et al., 2013) uses skeletal data to assess step time, step length, stride time, stride length and speed gait. The results show increased accuracy in stride length, step length and gait speed. (Auvinet et al., 2015) calculates spatiotemporal gait parameters based on the step length as a maximum distance between ankles, stride length by doubling the step length, and gait speed by using stride length over MS Kinects data rate. The authors use these features in biometric recognition using three different classifiers. (Dolatabadi et al., 2014) determine the two main phases of gait cycle (stance and swing) automatically from the movement of the ankle joint in the z-axis.

The spatiotemporal gait features can be calculated accordingly as the following equations illustrate:

$$Step\ length\ =\ Max\ _x(Reffoot_i - oppositefoot_i) \tag{1}$$

$$Stride\ length\ =\ Max_x\ (Reffoot_i - Reffoot_{i+1}) \tag{2}$$

$$Cycle\ time\ =\ HS_i - HS_{i+1} \tag{3}$$

$$Stance\ time\ =\ HS_i - TO_i \tag{4}$$

$$Swing\ time\ =\ TO_i - HS\ _{i+1} \tag{5}$$

$$Double\_sup\ T\ =\ (SH_i - TO_i)R \cap ((SH_i - TO_i)L \tag{6}$$

$$Cadence = number\ of\ step\ /\ time\ (min) \tag{7}$$

$$Speed\ =\ cadence\ \times\ step\ length \tag{8}$$

Where Max_x is the maximum distance between two heel's strikes in horizontal direction, i is the number of frames, HS is the heel strike, R for right foot, L for left foot and TO is the toe off, time represents time taken for the process whereas length is the distance covered by the skeletal joint motion during the walk as Fig.2 illustrates.

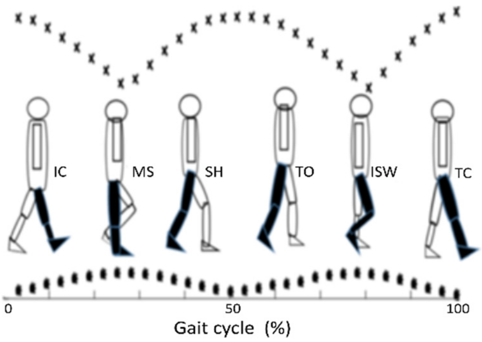


Figure 2: Detection of a complete gait cycle by tracking the distance between the left and right ankle joints (the top curve), and tracking the vertical displacement of the left and right hips (the bottom curve). The gait cycle contains; initial contact (IC), mid stance (MS), strike heel (SH), toe off (TO) and initial swing stages (ISW).

2.3 Classification Technique

Data classification techniques have been used in many different fields including human gait classification, representation and recognition using MS Kinect. In classification stage, researchers use different classifiers. The Nave Bayes Neural Network (NBNN) classifier is used in (Yang & Tian, 2012) for classifying the human actions using the skeleton data from MS Kinect. (Andersson & de Araújo, 2015) uses three types of classifiers for gait attributes using MS Kinect, the authors achieved the highest level of accuracy with SVM classifier, followed by k-NN classifier, and then with the MLP classifier. In (Arai & Asmara, 2014), 3D skeletal model is extracted by using MS Kinect video data to classify gait gender, and the result shows that 83.75% and 76.25% classification rate using SVM, Nave Bayes, respectively.

3 PROPOSED METHOD

3.1 Modified Gait Signal in Time Domain

The modified signal $M(t)$ is generated by multiplication of the reference signal to the gait signal g(t) for obtaining the relationship as in (9). The reference signal is chosen as a sinusoidal signal with fixed parameters $(\mathrm{Ac} = 1\ \mathrm{m}, f_c = 7.5\ \mathrm{Hz})$, these values let the spectrum of signals in the medial of the graph; this is related to the sensor data rate. While, gait signal g(t) is generated from the horizontal distance between ankles during walk.

$$\mathrm{M(t)} = \mathrm{Ac}\,(1 + \mathrm{D.g(t)}) \cos \mathrm{w_c}\ \mathrm{t} \qquad (9)$$

Where, D is the depth of modification and can be written as:

$$D = Ag\ /\ Ac \qquad (10)$$

Where Ag is the amplitude of the gait signal, which can be substituted by [1/2 $(Max\ p\_p)$ - 1/2 $(Min\ p\_p)$], while the amplitude of reference signal Ac can be replaced by [1/2 $(Max\ p\_p)$ + 1/2 $(Min\ p\_p)$], as Fig. 3 shows.

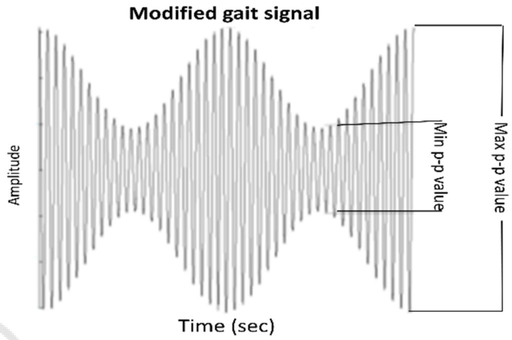


Figure 3: Modified gait signal using AM technique in time domain.

Finally, the depth of modification (D) in percentage can be obtained by dividing the amplitude of gait signal (Ag) over the amplitude of the reference signal (Ac), see (11).

$$D = [(Max\ p\_p) - (Min\ p\_p)] / [(Max\ p\_p) + (Min\ p\_p)] \times 100 \quad (\%) \qquad (11)$$

The modification depth (D) is extracted from $M(t)$ for three different kinds of walking speeds, as described in Algorithm 1.

Algorithm 1. Depth Modification (D):

```
Input:
Input 1 = Gait signal
Input 2 = Reference signal
Processing & Output:
D = Input1 amplitude
Input2 amplitude
while i <= N do
IF Speed = = Slow walk
then D-slow = D
else IF Speed = Normal walk
then D-normal = D
else
Speed = Fast walk
then D-fast = D
end IF
end while
```

3.2 Modified Gait Signal in frequency Domain

The spectrum of the modified gait signal on the frequency domain is achieved by using Fast Fourier Transformer to analyse the complex signal to its original components. The spectrum of modified gait signal consists of three components, namely upper side band component which has the highest frequency (w_c +w_g), lower side band component which located at the lowest frequency (w_c - w_g), and the middle component which is at w_c, as shown in Fig.4.

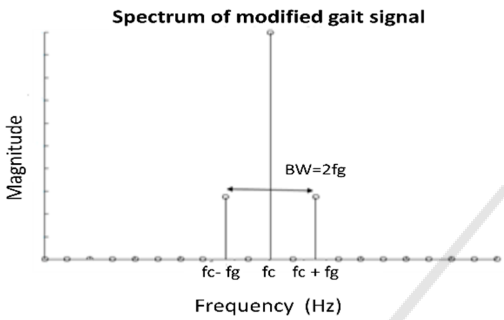


Figure 4: The spectrum of modified gait signal in frequency domain.

The spectrum of modification signal is extracted by using (9) which yields (12).

$$\mathrm{M(t) = A_c \cos w_c t + A_c \cos w_c t\ \ g(t)} \quad (12)$$

Where, the $g(t)$ is the gait signal, and can be written as, $g(t) = A_g \, cos \, w_g t$, to obtain the following equation:

$$M(t) = A_c \, cosw_c \, t + A_c \, cosw_c t \, . A_g \, cosw_g \quad (13)$$

Finally, by using the multiplication concept of cosine functions in (13), the components of the modified gait signal is formed as in (14). Where, the angular frequencies w_c, and $w_g$is simplified intof_c, and f_g respectively.

$$M(t) = A_c cos\, f_c + 1/2(A_c A_g \cos(f_c - f_g) + 1/2(A_c A_g \cos(f_c + f_g)) \quad (14)$$

Where f_c, is the frequency of the carrier signal, which is always constant, while f_g is the frequency of the gait signal which varies according to the number of gait cadence per a certain period of time. Algorithm 2 describes the baseband frequency implementation in detail which is related to the gait speed.

Algorithm 2. Baseband frequency (fg):

```
Input:
Input 1 = Gait signal @ fg
Input 2 = Reference signal @ fc
Processing & Output:
fg = BW/2
while I <= N do
For Speed = Slow walk do
IF (fc+fg @ max3) > fc @ max2 > (fc- fg
@ max1)
then f_slow = (fc+fg)-(fc-fg)
end IF
For Speed = Normal walk do
IF (fc+fg @ max3) > fc @ max2 > (fc- fg
@ max1)
then f_normal = (fc+fg)-(fc-fg)
end IF
For Speed = Fast walk do
IF (fc+fg @ max3) > fc @ max2 > (fc- fg
@ max1)
then f_fast = (fc+fg)-(fc-fg)
end IF
end while
```

4 EXPERIMENTAL RESULTS

4.1 Gait Signal Generation

The proposed method is developed using Matlab and tested on 14 healthy subjects who were instructed to walk in the front a MS Kinect. Each subject performed three types of walk speeds: slow, normal and fast walk. The positional data of left and right ankles is collected in each trial for all subjects as shown in Fig.5.

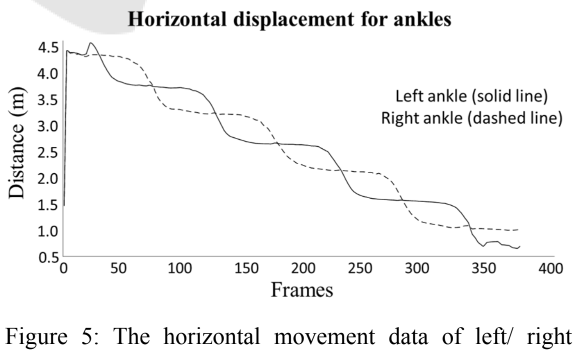
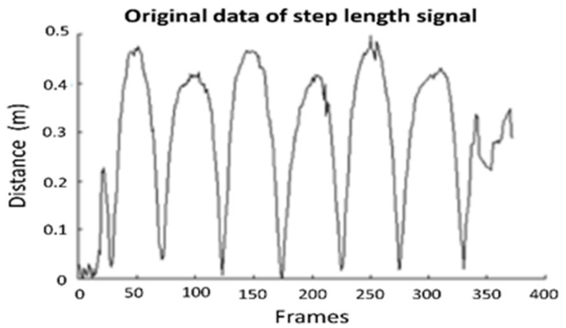


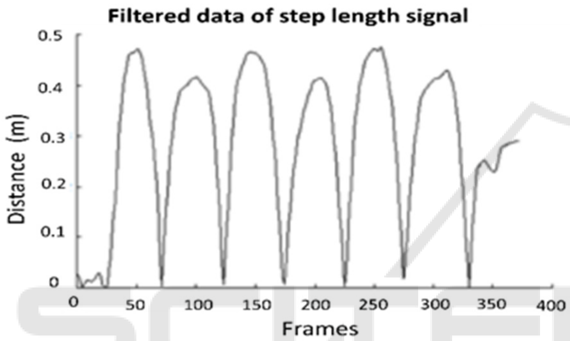
Figure 5: The horizontal movement data of left/ right ankles.

The horizontal distance between ankles during walk can generate the gait signal which is mentioned as unmodified signal $g(t)$ as can be seen in Fig.6, where the maximum value of $g(t)$ represents the gait step length in meter.

The RLOESS filter is used for smoothing the row joints position data. Fig.6 illustrates the difference between the row data in Fig.6 (a) versus the smoothed data in Fig.6 (b).



(a)



(b)

Figure 6: The step length signal: (a) original data; (b) filtered data.

4.2 Features Extraction

A complete and consistent gait analysis commonly requires the cycle gait determination, which can be divided into two phases; the stance and swing phases. Two different methods are used for extracting the gait features; both methods have been based on the lower limbs displacement data (positional data) to determine the gait features in three different kinds of the walking speeds. Method 1: spatiotemporal gait analysis based on the gait displacement signal. Method 2: proposed AM method based on the modified gait displacement signal.

The former method is used for extracting eleven gait features; step length, stride length, step width, left and right swing phase time, left and right stance phase time, gait cycle time, double support phase time, gait cadence and speed. These features are extracted by using equations (1-8) for all subjects in three different kinds of walk as shown in Fig. 7.

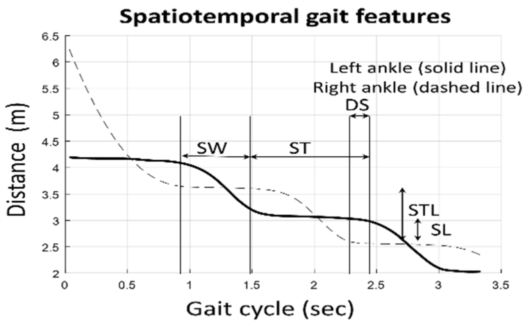


Figure 7: The determination of a complete gait cycle for extracting the step length (SL), stride length (STL), double support time (DS), swing time (SW), stance time (ST) and gait cycle time (SW+ST).

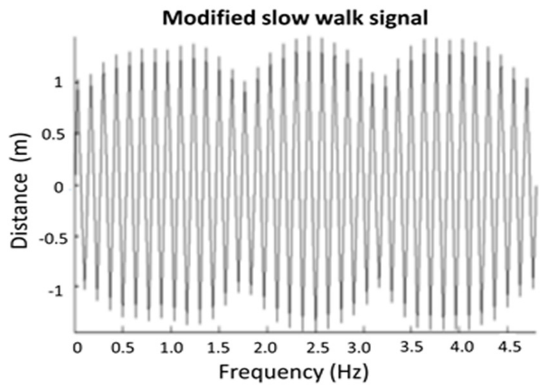
The latter method is used for extracting two parameters of the gait signal by modifying the gait signal using the AM technique. The modified gait signal can be represented in time domain to extract the modulation depth (D), which represents the ratio for the amplitude of the gait signal to the amplitude of the reference signal. The second parameter of the modified gait signal is the baseband frequency of the gait signal (fg) which can be extracted by representing the modified gait signal on frequency domain.

The baseband frequency (fg) can be found either in the lower or the upper side band component. The gait features have been extracted for all subjects on three types of walk speeds, as can be seen in Fig.8, Fig.9 and Fig.10.

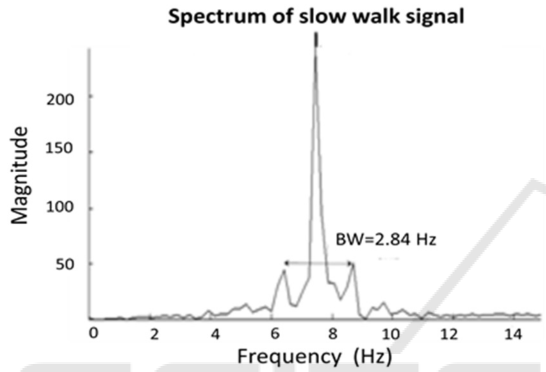
4.3 Classification and System Evaluation

In this set of experiments, the extracted gait features have been categorised into two groups relating to the method that is used for extracting the gait features; the first set of data is extracted the gait cycle using spatiotemporal gait analysis, whilst the second set of data is extracted by using the proposed AM technique.

The first data set including step length, stride length, stance phase time, swing phase time, double support phase time, cadence, and speed gait, the second data set include modulation index and baseband frequency of modified gait signal. DT, linear SVM, non-linear SVM, and k-NN classifiers are compared and we investigate the high predictive power of features. The task of a classifier is to predict three kinds of walking speeds in three classes (C1, C2 and C3) as listed in Table 1 for spatiotemporal gait analysis and Table 2 for the proposed AM method, respectively.

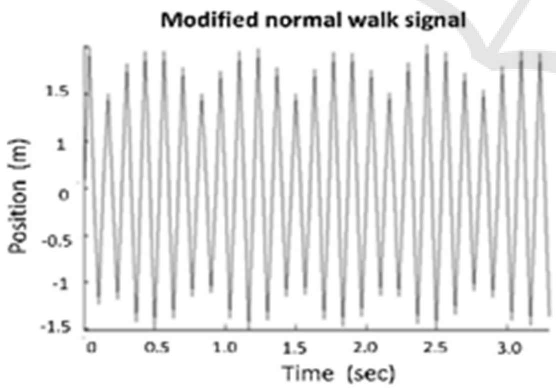


(a)

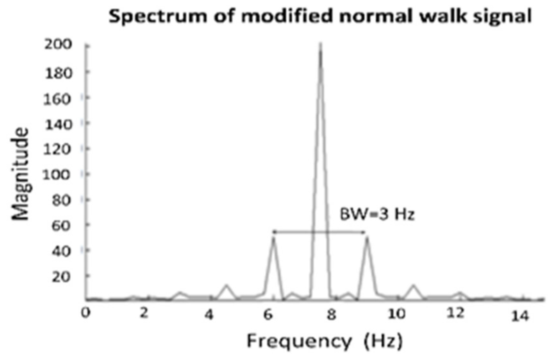


(b)

Figure 8: Modified gait signal during slow walk (a) Time domain representation. (b) Frequency domain representation.

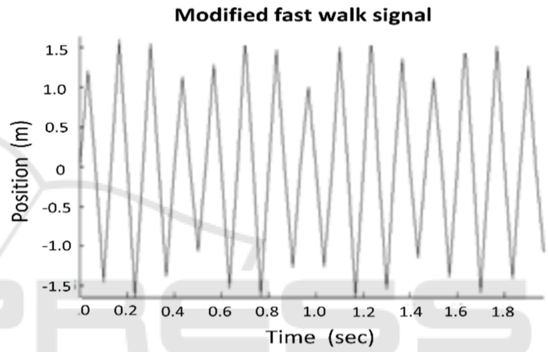


(c)

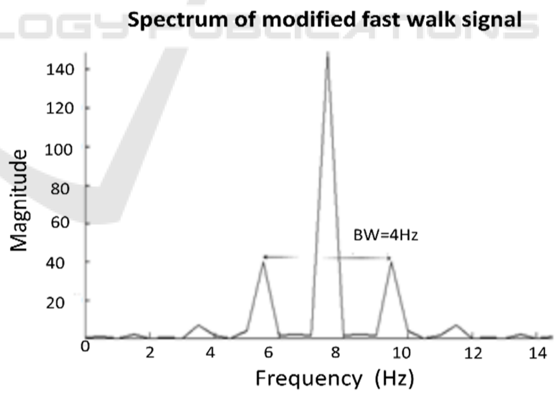


(d)

Figure 9: Modified gait signal during normal walk (c) Time domain representation. (d) Frequency domain representation.



(e)



(f)

Figure 10: Modified gait signal during fast walk (e) Time domain representation. (f) Frequency domain representation.

Table 1: Result of four different classifiers for spatiotemporal gait analysis method in three different kinds of walking speeds, the sensitivity and specificity are calculated for: slow speed (C1), normal speed (C2) and fast speed (C3).

Classifiers	Sensitivity			Specificity			Accuracy (%)
	C1	C2	C3	C1	C2	C3	
Decision Tree	1	1	1	1	1	1	100
Nonlinear SVM	1	0.93	0.93	1	0.93	0.93	97.6
Linear SVM	1	0.86	0.93	1	0.96	0.93	95.2
k-NN	1	0.93	0.93	1	0.96	0.96	95.2

Table 2: Result of four different classifiers for spatiotemporal gait analysis method in three different kinds of walking speeds, the confusion matrix and AUC curve are calculated for: slow speed (C1), normal speed (C2) and fast speed (C3).

Classifiers	Confusion matrix			AUC			Overall error (%)
	C1	C2	C3	C1	C2	C3	
Decision Tree	0	0	0	1	1	1	0
Nonlinear SVM	0	0	7.1	1	1	0.982	2.4
Linear SVM	0	0	14.3	1	1	0.997	4.8
k-NN	0	0	14.3	1	0.964	0.982	4.8

Table 3: Result of four different classifiers for modified gait signal technique in three different kinds of walking speeds, the sensitivity and specificity are calculated for: slow speed (C1), normal speed (C2) and fast speed (C3).

Classifiers	Sensitivity			Specificity			Accuracy (%)
	C1	C2	C3	C1	C2	C3	
Decision Tree	1	1	1	1	1	1	100
Nonlinear SVM	1	1	1	1	1	1	100
Linear SVM	1	1	1	1	1	1	100
k-NN	1	0.93	1	0.94	1	1	97.6

Table 4: Result of four different classifiers for modified gait signal technique in three different kinds of walking speeds, the confusion matrix and AUC curve are calculated for: slow speed (C1), normal speed (C2) and fast speed (C3).

Classifiers	Confusion matrix			AUC			Overall error (%)
	C1	C2	C3	C1	C2	C3	
Decision Tree	0	7.1	0	1	1	1	0
Nonlinear SVM	0	0	0	1	1	1	0
Linear SVM	0	0	0	1	1	1	0
k-NN	0	7.1	0	0.982	0.964	1	2.4

4.4 Discussion

Sensitivity, specificity, accuracy, overall error, confusion matrix and AUC have been shown for various classifiers which used in this paper. It is noticeable that the Decision Tree (DT) classifier achieves the best results in both techniques with accuracy 100% as shown in tables' result. In addition, the sensitivity and specificity have been shown high predictive result with class one which represents the slow walking speed for both techniques, they reached 1. This means the ability of classifiers to sense the positive value correctly (sensitivity), and ability to select the negative value correctly (specificity). Moreover, the classification accuracy for the proposed method showed higher result than spatiotemporal gait analysis, where the former method reached 100% with three different classifiers, while the latter method reached 100% just with DT classifier as shown in tables (1 & 3). However, the k-NN classifier showed the lowest classification accuracy in both techniques, but still the proposed method has better result than another method as 97.6% and 95.2%, respectively.

In tables (2 & 4), AUC evaluation metric showed better results with the modified gait signal technique than the spatiotemporal gait method, where the proposed method reached 1 with three types of classifiers, while the spatiotemporal analysis method reached 1 just with decision tree classifier for all classes. The confusion matrix used to calculate the false negative rate reported only 7.1% with AM method, and 14.3% with spatiotemporal gait analysis.

5 CONCLUSIONS

In this paper, we study the concept of classifying the assessment of three types of gait speeds by using 3D human skeleton for lower joints' body position which is captured by a Kinect v2 sensor. We propose an enhanced gait features extraction which is based on a positional lower joints data without the requirement of the gait cycle determination.

The proposed method shows high classification accuracy using several classifiers in comparison to spatiotemporal gait features method. The high predictive power of classifier can be related to the extracted features which are based on the modified gait signal that was generated by amplitude modulation technique. In the system evaluation, the confusion matrix and receiver operating characteristics (ROC) curve is used for calculating the accuracy, sensitivity, specificity and area under curve (AUC). The proposed method increased classification efficiency as opposed to spatiotemporal gait analysis which uses evaluation metrics (accuracy, sensitivity and specificity) to evaluate each classifier's result.

ACKNOWLEDGEMENTS

We thank Libyan government for supporting this research financially.

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