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# Gait Recognition based on Measurements of Moving Human Legs Angles

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*A B S T R A C T*

Biometrics plays a crucial role in security systems. Gait recognition as an aspect of behavioral biometrics deals with identifying human based on the walking. In this research, we proposed a new method to identify people according to their gait characteristics. This approach is performed via several steps; a) the video frames of a walking subject is recorded. b) each video is decomposed into eight phases, wherein each phase, there are several frames. One frame per phase is selected. c) the extracted frame is segmented to separate the subject from the background. d) the image is converted to a binary image, and the skeletonization is applied to obtain the silhouette of the image. e) the fast Fourier transform is applied to each frame, and several statistical features are calculated. The average of the statistical measures for eight frames of a video is computed as a feature vector for the subject. Finally, the correlation is used to identify the subject based on the feature vector. The accuracy of 100% is achieved for the recognition of the subjects in the CASIA dataset.

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## 1. INTRODUCTION

In the form of identity access management, access control, and individual identification in the surveillance area, biometric algorithms are the best method for monitoring and human identification. [1]. These methods have been used for uniquely recognizing people based on one or more intrinsic physical or behavioral features [2]. So, depending on these features, biometric can be divided into two main classes [3]:

- Physiological biometrics that are based on a person's physical characteristics, including fingerprint, face, iris, retina, palm print, DNA, and hand geometry recognition [4].
- Behavioral biometrics that are based on doing or acting of unique ways of people, including typing rhythm, voice, signature, and gait recognition [5].

    Biometric frameworks for recognizable human proof at separation have been an expanding request in different critical applications [6]. Various biometric assets, for example, iris, unique mark, face, palm print, hand geometry, have been contemplated efficiently and

utilized in numerous frameworks [7]. Regardless of their board applications, these assets experience the ill effects of adjustment of low-goals pictures, and the need of clients to participate for precise outcomes [8]. Recently, innovative biometric acknowledgment techniques for remote human ID have been a dire requirement for observation applications and have pulled in enormous consideration among analysts in the computer vision network [9]. In the early 1990s, many efforts of gait recognition for human identification were studied using different methods in the field of computer vision, so using gait recognition as a biometric was considered a relatively new area of study [10]. In this modern era, the joining of human movement examination and biometrics has entranced a few security-delicate situations, for example, military, wellbeing, banks, parks, air terminals, and so forth [11].

    The problem of gait recognition is one of the major problems facing biological measurements because the nature of human movement cannot be stable. Thus, this leads to the failure in reaching accurate results in the real world.

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## 2. THEORETICAL BACKGROUND

Biometric is defined as physiological or behavioral characteristics that are used to identify and verify the identity of the human individual [12]. It is clear that walking is the most convenient way to travel short distances [13]. How to recognize the style of walking in an efficient way leads to gait recognition [14]. Gait is a behavioral characteristic that deals with the particular style or manner of walking, stepping, and running of a human body [15].

Gait characteristics are used for human recognition that can be classified into two categories, static and dynamic [16]. Static features reflect measurements based on the geometry of the anatomical structure of the human body, such as size, length, and width of the different body segments [17]. Static features can also be derived from the observed approximation, such as stride length, while dynamic characteristics are the indices describing the kinematics of the locomotion process as the angular movement of the lower limbs that extracts articular trajectory data [18]. Recent research on the approach using static features for identification has shown that a promising recognition rate can be achieved [19]. On the other hand, some researchers preferred to combine static and dynamic indeces by believing that the fusion would give the optimal recognition rate [20].

The normal forward gait step consists of two phases [21]: stance phase and swing phase. In the former phase, a leg and a foot carry most or all of the body weight. The stance is comprised of five gait steps (initial contact, loading response, mid stance, terminal stance, and pre-swing). In the laterphase, the foot does not touch the surface of the walk, and the weight of the body is supported by the other leg and foot. Swing is comprised of three steps occurring during the swing.

The eight phases of the human gait cycle can be described as below (see Figure 1) [22]:
**1.** Initial Contact (IC), this phase takes 0 % part of the gait cycle, in which heel contact with the ground.
**2.** Loading Response (LR), this phase takes 0 – 12 % part of the gait cycle, with shock absorption in the knee and ankle joint.
**3.** Mid Stance (MST), this phase takes 12 – 31 % part of the gait cycle, which controls the forward motion of the tibia.
**4.** Terminal Stance (TST), this phase takes 31 – 50 % part of the gait cycle, in which controlled dorsal extension at the ankle joint with lifting the heel from the ground.
**5.** Pre Swing (PSW), this phase takes 50 – 62 % part of the gait cycle, with passive knee joint flexion of 40°.
**6.** Initial Swing (ISW), this phase takes 62 – 75 % part of the gait cycle, in which a minimum 55° knee flexion for sufficient.

**7.** Mid Swing (MSW), this phase takes 75 – 87 % part of the gait cycle, in which increasing hip flexion to 25°.
**8.** Terminal Swing (TSW), this phase takes 87 – 100 % part of the gait cycle, in which knee joint extension to neutral-flexion.

Many methods were implemented for the gait recognition process, but most of these methods [23] unite in that they adopt the following steps in the processing system [24]. The general steps of gait recognition system are given as below [25]:
•    Preprocessing module: it is the first step in many computer vision applications that aims to accurate retrieval in order to minimize distortion as possible. This process includes; noise reduction, enhancement of the signal, detecting the moving person, tracking the moving person, background subtraction, and silhouette extraction, then normalizing and scaling [26].
•    Feature extraction module: it is an important step that needs to choose which features to be extracted and how it can be applied. This process includes gait cycle detection, spatiotemporal correlation, and similarity computation [27].
•    Pattern classification module: this process deals with measuring the distances in some space in which the patterns have been represented [28,29].
•    Decision making: in this step, the decision is made according to the obtained information to identify the person [30,31].

## 3. LITERATURE REVIEW

Many attempts have been made in human gait recognition, and some approaches have been developed over the last few years.
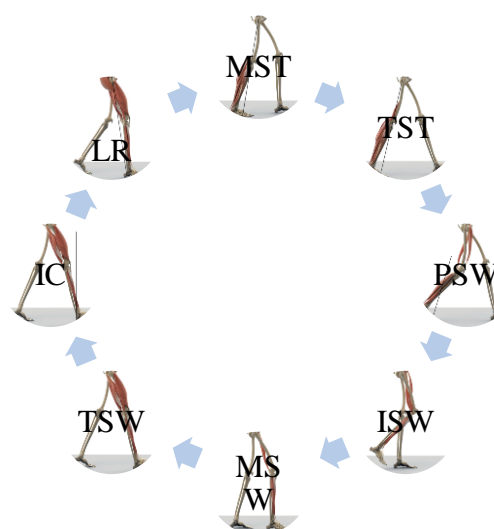


**Figure 1.** Eight phases of the human gait cycle

Dupuis et el. [32] addressed the problem of recognition based on the modeless approach. They proposed an approach based on Random Forest to solve the problem of the space of characteristics of high dimensional space. To perform an efficient search in the subspaces, they applied a search strategy to eliminate the functionality in the background. The primary experiments were carried out under unknown covariant conditions. The experimental results showed that the proposed mask provides satisfactory results for all angles of the probe with the unspecified view.

Lee et el. (2013) proposed a framework for gait recognition through different points of view and walking conditions based on sequences of approaches collected from several points of view. They developed a new multivariate subspace representation approach that considered the gestural sequences collected from different views of the same subject, and a linear subspace is extracted to describe the set of entities. The methods of representation of entities based on the subspace, measure the differences between samples, and can manage certain variations between subjects. Experimental results from a widely used multi-view database are presented to demonstrate the effectiveness of the proposed framework [33].

Aqmar et el. [34] described a gait recognition approach by suppressing and using gait fluctuations. Inconsistent synchronization between a pair of walking image sequences due to temporal fluctuations degrades the gait recognition performance. They eliminated temporal fluctuations by generating a sequence of gait images with equal phase intervals. If fluctuations between periods of gait in a sequence of gait images are observed several times for the same subject, that may be considered a feature of a useful distinctive approach. They evaluated the methods in experiments using large public databases and demonstrated the effectiveness of the proposed methods.

Zeng et el. [35] introduced a strategy for perceiving the silhouette-based methodology through a deterministic learning hypothesis that consolidates the qualities of space-time development and the physical parameters of a human subject by means of breaking down the shape parameters of the form of the silhouette. It has been approved distinctly in groupings with a sidelong view recorded in the research facility. They represented the dynamics of the walking motion and can more effectively reflect the small variation between different walking patterns. The walk acknowledgment approach comprises of two stages: a training stage and a test stage. In the training stage, the elements of the step fundamental the individual methodologies are moved toward locally through systems of outspread capacities through deterministic learning hypothesis.

Chattopadhyay et el. [36] utilized Kinect depth data to address the issue of the impediment in frontal rigging

acknowledgment. They considered circumstances where such profundity cameras are mounted on the passage and leave purposes of an observed zone, individually catching the back and frontal perspectives regarding each matter going through the region. A lot of qualities compared to the back view are obtained from the profundity data along with the form of the outline, while the occasional variety of the skeletal structure of the lower area of the body evaluated by Kinect is removed from the front view. These highlights accomplish high-goals driving elements and can be proficiently removed. This technique is electronic and demonstrated empowering results at various degrees of impediment.

Lee et el. [37] accomplished a mix of spatiotemporal methodologies and surface descriptors to extricate fleeting models in strolling cycles. Not at all, like most regular techniques that attention on spatial data while constraining caught worldly data, spatiotemporal strategies save spatial and fleeting data. The proposed technique likewise develops surface descriptors of walk development after a while. For every stride cycle, they examined the parallel pixel models along with the time hub, called transient double models. The exploratory outcomes unmistakably indicated the prevalence of this methodology contrasted and different strategies.

Yang et el. [38] focused on human recognition with the gait characteristic obtained by Kinect and achieve that the walking trait can effectively distinguish different humans through an original representation of gait characteristics. The experimental results showed that the precision of the recognition with relative distance characteristics reached up to 85%, which is comparable to that of the anthropometric characteristics. The combination of relative distance characteristics and anthropometric characteristics can provide an accuracy of more than 95%. The results indicated that the relative distance characteristic is very efficient and deserves to be studied in more detail with more general scenarios.

Deng et el. [39] proposed a robust approach to the recognition of gait through the fusion of multiple views and deterministic learning. This approach presented a multi-view fusion strategy that the gaits collected under different points of view are synthesized as a kind of synthesized silhouette image. Then the synthesized silhouettes are characterized by many types of gait characteristics that vary over time, which include three silhouette width characteristics and the feature of the silhouette area. In addition, the variability of the underlying approach to gait characteristics that varies over time from different individuals is effectively modeled using a deterministic learning algorithm. Experimental results showed that the accuracy of the recognition is acceptable.

Deng et el. [40] portrayed a methodology of step acknowledgment by the mix of the attributes of the space-time and kinematic stride. The binary silhouettes of each

walking sequence are specified by a holistic silhouette area and three lower extremity silhouette widths. The spatiotemporal approach features can be obtained as the path dynamics underlying the width trajectories of the lower limbs and the holistic zone of the silhouette, indicates the temporal changes of the silhouette. At that point, a model-based methodology is proposed to separate the directions of the specific edges of the lower limits. The qualities of the kinematic approach can be spoken to as the elements of the hidden course of articular points, which spoke to the transient changes in the structure and elements of the body.

Deore et el. [41] proposed a method to recognize the human gait of multiple views that used partial wavelet coherence as a new feature. Euclidean distance representation, one-dimensional signals generated by the movements of the hands, legs, and shoulders of the multiview process sequences, preserves the temporal and spatial information of individual works. This method retrieves dynamic information directly without using a template. The obtained results indicated the average recognition accuracy was 73.26% when considering only the partial wavelet coherence functionality. The phase feature is used to retain the discriminant information of the dynamic phase angle between the body parts. Companied partial wavelet coherence with the phase feature system improved the performance with an average recognition accuracy of 82.52%.

Gadaleta et el. [42] presented a framework to authenticate users from movement signals acquired by smartphones. They proposed a way to deal with perceive objective clients of their walking, utilizing the accelerometer and inertial signs given by a business cell phone utilized in the front pocket of the client. .In this multi-step authentication method, the convolutional neural networks (CNN) was used for feature extraction and the support vector machine (SVM) to classify walking cycles and their coherent integration [42]. This framework works on a profound learning approach and separate all-inclusive highlights for acknowledgment of the methodology joining the aftereffects of the grouping of consequent run cycles into a multi-arrange dynamic system.

## 3. MATERIAL AND METHOD

In the following, first, we introduce the dataset used in the research, then we provide the mathematical model for a moving leg angles, finally, the proposed method is explained.

**3. 1. Gait Image Data Set**          Gait recognition has been a functioning exploration subject in recent years. The Institute of Automation, Chinese Academy of

Sciences (CASIA) provided the CASIA gait database for gait recognition and related researches. In the CASIA gait database, there are three databases, the normal gait single-view image database, the multi-view image database, and the infrared image database. This paper is concentrated on the normal gait single-view image database that includes various gait videos in which reconstructed from around 70 frames. In addition, each video includes three cycles that take about 10 seconds, which means each cycle required about 3 seconds. In addition to the identification of the exact frame for each phase, the most important task is to find and catch the starting and ending frames of each cycle.

**3. 2. Moving Leg Angles**          The thigh and leg are represented through straight lines for each of them as the thinning operation occurs (Figure 2). These lines are analyzed in different ways. The angle of thigh could be as an angle between the straight line of the thigh and the horizon, as well as the angle of the leg could be measured as an angle between the straight line of the leg and the extended line of the thigh.

Consider the two points $(x1,y1)$ and $(x2,y2)$, the distance between these two points is:

$$D = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \tag{1}$$

The slope between these two points is:

$$Slope = \frac{y_2 - y_1}{x_2 - x_1} \tag{2}$$

The distance between the indicated line and the origin is:

$$\rho = x\cos(\theta) + y\sin(\theta) \tag{3}$$

where $\theta$ is the angle formed between the X-axis and the perpendicular line of the leg.

This paper is concentrated on the human gait recognition via recognition of lines and angles of legs.

To get a silhouette of pixel-wide lines, the skeleton is taken from a silhouette through a set of morphological operations. The result pixels will be approximately equidistant from the boundary of the initial object.
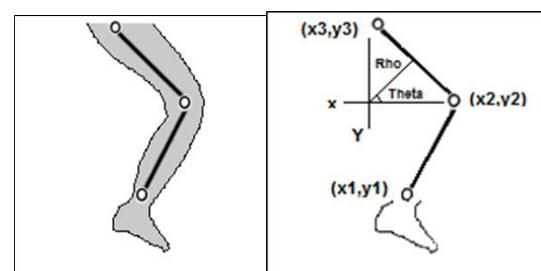


**Figure 2.** Leg and thigh lines.

**3. 3. Proposed Gait Recognition Algorithm**
Human walking represents a specific pattern for each person. This work is concentrated on gait recognition pattern in order to generate specific features for the represented person. This approach is implemented via the following steps (Figure 3):

- Video acquisition: capture the videos within a certain time (about 20 seconds) from a fixed camera within an adequate background. These videos are prepared to contain at least two or three gait cycles within 10 seconds.
- Frame extraction: convert the videos into frames at a rate of seven frames per second, so at the end, there are about 75 frames of the overall video. Then create eight phases where each phase composed of several frames. Lastly, one frame from each phase is selected. As a result, eight frames are extracted per video.
- Frame preprocessing: eliminate the unwanted noise from the frames by applying a median filter that reduces the noise without affecting the data.
- Frame segmentation: separate the image into two parts; object and background. A background subtraction is applied to separate the object from the background. In this approach, the intermediate frame is subtracted from the initial frame which is just the background. The background pixel remains same in both the frames, so in the subtraction it will become zero but the pixel value in the subject's body is different in pixel value from the background, so it will result in non-zero pixels. If the result of the subtraction is above a certain threshold then the frame is considered as containing the human gait.
- Binary image: convert the frames into binary images.
- Silhouette detection: A morphological operation, skeletonization, on the binary image creates a new binary image in which the pixel has a non-zero value only if the test is successful at that location in the input image. The morphological operation is applied to binary images to detect the Silhouette of the object.
- Feature extraction: it is an important step to generate features that are used for recognition and classification. Several statistical features are calculated from fast Fourier transform (FFT) of Skeleton images such as standard deviation, mean, median, max, and min values. For each video, eight frames are considered and the average of the statistical features is calculated the feature vector.
- Classification: Finally, the correlation between the feature vector from the subject and the stored feature vectors in the dataset is calculated. The maximum correlation indicates the identified subject. A threshold can be selected based on the average

correlations between the features obtained from the dataset.

## 4. ANALYSIS AND DISCUSSION

In gait recognition, two important aspects must be localized to ensure that your procedure goes in the correct direction. These aspects are:

- Detecting the starting frame of each gait cycle and finding the number of frames in each cycle.
- Detecting the starting frame of each phase within the cycle and finding the number of frames in each phase.

Several gait videos were recorded to be used in gait recognition, and these videos were extracted into frames, so a big amount of data (frames) are ready to be processed. So it is important to reduce and determine the size of the problem in order to achieve a reasonable result. To ensure that aspect, it is important to extract the frames. The extracted frames from gait video were collected in a certain image data set, as shown in Table 1. These frames were numbered to identify the gait cycle and phases in each cycle. This table shows 75 frames extracted from the gait video. However, we used one frame per phase results in 8 frames to reduce the computational cost of the method.

Each video consists of three gait cycles (C1, C2 & C3) and is decomposed to 75 frames. There are eight gait phases of each cycle (IC-P1, LR-P2, MST-P3, TST-P4, PSW-P5, ISW-P6, MSW-P7 & ISWP8) as illustrated in Table 1. In addition, this table indicates the starting frame of each phase.

Generally, there are two types of gait processing; one concerns with the complete gait cycle and the other concerns with the half gait cycle. The implemented approach considers the complete gait cycle (that has the eight gait phases) as it provides comprehensive data for processing.

In the first phase, Initial Contact (IC) is located at frame number 5. Figure 4 shows this phase where the original frame image is converted into a binary image, edge image, and skeleton image; these are shown in Figure 4(a, b, and c), respectively. Figure 4(d) represents the FFT of the skeleton image. These statistical values of standard deviation=7.6477, mean=8.0940, median=6.3504, max=248, and min approach to zero.

The second phase, Loading Response (LR), is located at frame number 8, in which the original frame image is converted into a binary image, edge image, and skeleton image. The statistical measures are of standard deviation=6.7145, mean=6.8859, median=5.2465, max=185, and min approach to zero.

The third phase Mid Stance (SST), is located at frame number 18, in which the original frame image is converted into a binary image, edge image, and skeleton

**TABLE 1.** Gait cycles and phases of a certain video

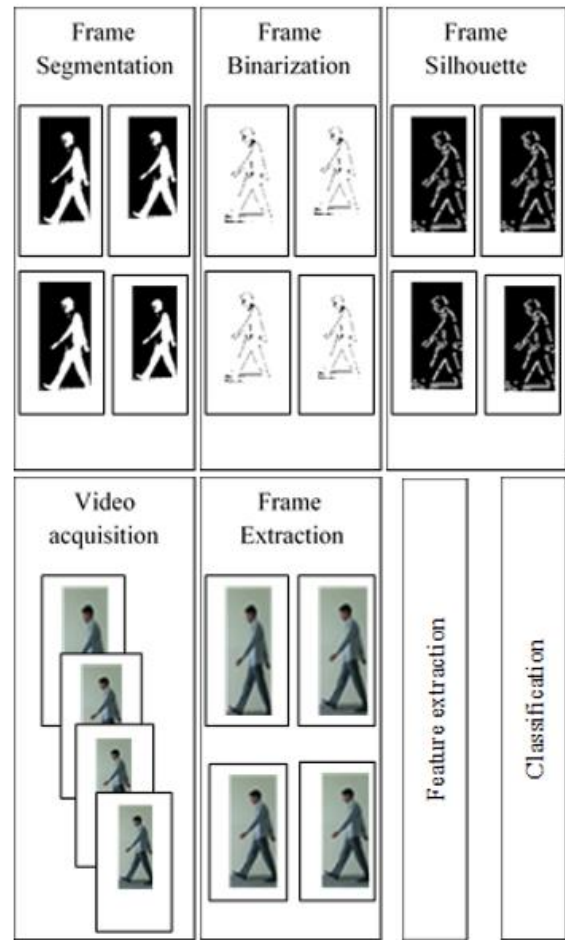| Cycle Number | Phase Number | Frame Number |
|---|---|---|
| C1 | IC-P1 | F05 |
| | LR-P2 | F08 |
| | MST-P3 | F18 |
| | TST-P4 | F20 |
| | PSW-P5 | F21 |
| | ISW-P6 | F23 |
| | MSW-P7 | F31 |
| | ISW-P8 | F33 |
| C2 | IC-P1 | F34 |
| | LR-P2 | F35 |
| | MST-P3 | F45 |
| | TST-P4 | F47 |
| | PSW-P5 | F48 |
| | ISW-P6 | F51 |
| | MSW-P7 | F58 |
| | ISW-P8 | F60 |
| C3 | IC-P1 | F61 |
| | LR-P2 | F62 |
| | MST-P3 | F70 |
| | TST-P4 | F72 |
| | PSW-P5 | F73 |
| | ISW-P6 | F75 |
| | MSW-P7 | - |
| | ISW-P8 | - |



**Figure 3.** Proposed gait recognition algorithm.

image. The statistical measures are of standard deviation=7.3126, mean=8.0948, median=6.3524, max=238, and min approach to zero.

The fourth phase, Terminal Stance (TST), is located at frame number 20, in which the original frame image is converted into a binary image, edge image, and skeleton image. The statistical measures are of standard deviation=7.1540, mean=7.8307, median=6.1442, max=225, and min is exactly zero.

The fifth phase Pre-Swing (PSW), is located at frame number 21, in which the original frame image is converted into a binary image, edge image, and skeleton image. The statistical measures are of standard deviation=7.0832, mean=7.6700, median=5.9824, max=218, and the min approaches to zero.

The sixth phase Initial Swing (ISW), is located at frame number 23, in which the original frame image is converted into a binary image, edge image, and skeleton image. The statistical measures are of standard deviation=6.4714, mean=6.6799, median=4.9969, max=173, and the min is exactly zero.

The seventh phase Mid Swing (MSW), is located at frame number 31, in which the original frame image is converted into a binary image, edge image, and skeleton image. The statistical measures are of standard deviation=7.0292, mean=7.6545, median=5.9701, max=216, and the min is exactly zero.

The eighth phase, Terminal Swing (TSW), is located at frame number 33, in which the original frame image is converted into a binary image, edge image, and skeleton image. The statistical measures are of standard deviation=6.8658, mean=7.1667, median=5.4480, max=197, and the min approaches to zero.

Table 2 shows the statistical measures of the complete gait cycle, including the eight phases. This Table indicated many statistical measures are calculated from FFT of Skeleton images such as standard deviation, mean, median, max, and min values. These values are measured precisely to indicate the starting frame of each phase.

Table 3 compares the performance of the proposed method with other state-of-the-art works in human gait

recognition problem. Although most of the developed methods provide high performance, the proposed method gives the best.

Traditional method can be divided into two folds: model based and holistic [43-46]. Model-based approaches fit models to extract suitable features that explain the dynamics of the gait. Parameters such as trajectories are measured according to the model being used. However, the performance of these methods is still limited due to the imperfect vision techniques in body structure/motion modeling and parameter recovery from a walking image sequence. Holistic methods locate the subject in the set of images. These methods demand high computational cost because they do not recover a structural model of human motion.

The time complexity of the proposed method is mainly related to the skeletonization and applying the FFT on the grayscale image. The time complexity of skeletonizatin is $O(m)$ where $m$ is the number of polygonal figure vertices and for the FFT is $O(n$ log
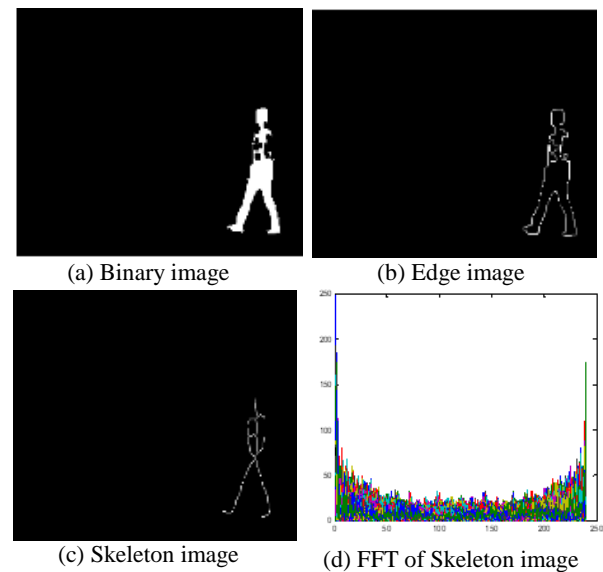


(a) Binary image          (b) Edge image

(c) Skeleton image     (d) FFT of Skeleton image
**Figure 4.** Analysis of frame No.5 (IC-P1)

**TABLE 2.** Statistical measures of the complete gait cycle

| Phase No. | Frame No. | Std. | Mean | median | Max | Min |
|---|---|---|---|---|---|---|
| IC-P1 | F05 | 7.6477 | 8.0940 | 6.3504 | 248 | $0.3390*10^{-3}$ |
| LR-P2 | F08 | 6.7145 | 6.8859 | 5.2465 | 185 | $0.1195*10^{-3}$ |
| MST-P3 | F18 | 7.3126 | 8.0948 | 6.3524 | 238 | $0.1045*10^{-3}$ |
| TST-P4 | F20 | 7.1540 | 7.8307 | 6.1442 | 225 | 0 |
| PSW-P5 | F21 | 7.0832 | 7.6700 | 5.9824 | 218 | $0.1468*10^{-3}$ |
| ISW-P6 | F23 | 6.4714 | 6.6799 | 4.9969 | 173 | 0 |
| MSW-P7 | F31 | 7.0292 | 7.6545 | 5.9701 | 216 | 0 |
| ISW-P8 | F33 | 6.8658 | 7.1667 | 5.4480 | 197 | $0.0502*10^{-3}$ |

**TABLE 3.** The performance comparison for different methods

| Research | Method | Accuracy (%) |
|---|---|---|
| [32] Y. Dupuis, X. Savatier, P. Vasseur (2013) | Random forest | 85 |
| [33] Chin Poo Lee, Alan W.C. Tan, Shing Chiang Tan (2013) | Interpolated deformable contour | 85 |
| [34] Muhammad Rasyid Aqmar, Yusuke Fujihara, Yasushi Makihara, Yasushi Yagi (2014) | Morphological technique | 70 |
| [35] Wei Zeng, Cong Wang, Feifei Yang (2014) | Silhouette | 90 |
| [36] Pratik Chattopadhyay, Shamik Sural, Jayanta Mukherjee (2015) | Kinect depth | 75 |
| [37] Chin Poo Lee, Alan W.C. Tan, Shing Chiang Tan (2015) | Transient binary pattern | 90 |
| [38] Ke Yang, Yong Dou, Shaohe Lv, Fei Zhang, Qi Lv (2016) | Kinect skeleton | 95 |
| [39] Muqing Deng, Cong Wang, Qingfeng Chen (2016) | Deterministic learning | 90 |
| [40] Muqing Deng, Cong Wang, Fengjiang Cheng, Wei Zeng (2017) | Fusion of spatial-temporal | 90 |
| [41] Sagar Arun More, Pramod Jagan Deore (2017) | Discrete wavelet transform | 82 |
| [42] Matteo Gadaleta, Michele Rossi (2018) | Convolutional neural network | 94 |
| **The proposed method** | **Silhouette and FFT** | **100** |

n) where n is the numer of row in a square matrix. As a result the time complexity of the method is O(m+n log n). Since, there are only five features, the complexity of the correlation function is negligible.

## 5. CONCLUSIONS

Gait recognition is an important biometric measure that has been applied in many applications, including medical, social, and security issues, specifically, it is a useful approach in contactless identification. In this work, we developed a new approach for human gait recognition based on fast Fourier transform and silhouette features extracted from video frames of subjects during walking. The simple correlation function is used to match the features corresponding to the subject in the dataset. A high-performance recognition rate (100%) was obtained by applying the proposed approach on CASIA database, which is a significant improvement compared to the other approaches. The performance of the proposed method owns to the well-designed algorithm for gait feature extraction based on spectral content of the images and partially benefits the Silhouette images  as they are invariant to changes in clothing color/texture and also lighting condition.

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## Persian Abstract

چکیده

بیومتریک نقش مهمی در سیستم های امنیتی دارد. شناخت راه رفتن به عنوان جنبه ای از بیومتریک های رفتاری، به شناسایی انسان بر اساس نحوه ی راه رفتن می پردازد. در این تحقیق ، روش جدیدی را برای شناسایی افراد با توجه به ویژگی های راه رفتن ارائه داده ایم. این روش شامل مراحل استخراج فریم، استخراج خط، اندازه گیری زاویه، استخراج ویژگی های مبتنی بر تبدیل سریع فوریه و اندازه گیری های آماری می باشد. سرانجام ، افراد با استفاده از اندازه گیری همبستگی بردارهای ویژگی استخراج شده طبقه بندی می شوند. دقت ۱۰۰٪ برای شناخت موارد آزمایش شده در مجموعه داده CASIA بدست آمده است.