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Research Paper

View-Invariant and Robust Gait Recognition Using Gait Energy Images of Leg Region and Masking Altered Sections

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Abstract: There are two serious issues regarding gait recognition. The first issue presents when the walking direction is unknown and the other one presents when the appearance of the user changes due to various reasons including carrying a bag or changing clothes. In this paper, a two-step view-invariant robust system is proposed to address these. In the first step, the walking direction is determined using five features of pixels of the leg region from gait energy image (GEI). In the second step, the GEI is decomposed into rectangular sections and the influence of changes in the appearance is confined to a small number of sections that could be eliminated by masking these sections. The system performs very well because the first step is computationally inexpensive and the second step preserves more useful information compared to other methods. In comparison with other methods, the proposed method shows better results.

Keywords: Biometrics, Gait Energy Image (GEI), Gait Recognition, Principal Component Analysis (PCA), Robust Recognition.

1 Introduction

BIOMETRIC traits of individuals are unique and people can be identified using these traits. The well-known traits are fingerprint and iris which are often used to identify people. These biometric traits yield a very good recognition rate, however, they entail subject satisfaction and a controlled environment. They are also difficult to be acquired from a distance [1]. Weight, height, and gender are soft biometric traits that are investigated to address these issues. These biometric traits can be captured remotely without the cooperation of the subject. However, they are not personal enough to exclusively identify a user. To address this problem, other biometric traits were introduced. Of these, a popular biometric trait is a gait [2].

There are many different methods of gait recognition [3]. These include methods that extract unique features of gait from the force generated by the soles of the foot on the sensor plate or the shoes with the sensor and also methods that depend on wearing movement recording sensors. The problem is that these methods are limited to controlled situations because the user or environment must be configured with the recorder. Along with the mentioned methods, some methods simply use video sequences and extract silhouettes from these sequences. One of these popular formats is the gait energy image (GEI) which calculates the average of silhouettes during a gait cycle and produces a template from the gait [4]. Other methods have also been developed to work on one walking direction sequence (for example lateral) where this issue is considered as an environmental constraint [5, 6].

As you know, the subject is examined in real environments without any limitations. So, to get a more realistic application, we have to consider two things in the application:

- Walking direction: mismatch of viewpoint between test data and database causes a lower recognition rate.
- Subject appearance: changing clothes and carrying a bag will change the subject's appearance, and these changes will reduce the recognition rate [7].

There are several articles to tackle each of these challenges, but there are few articles that tackle both.

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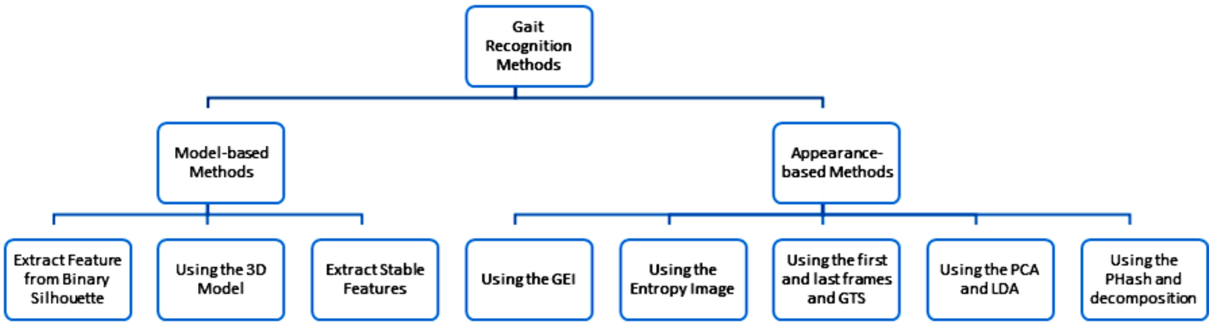

Fig. 1 Related works to address existing challenges in gait recognition.

2 Related Works

As can be seen in Fig. 1, from the beginning until now, the basic methods of gait identification are mainly divided into two sets:

- Model-based methods, and
- Appearance-based methods.

2.1 Model-Based Methods

The model-based methods identify subjects by modeling their specific properties using basic mathematical structures.

2.1.1 Extract Features from Binary Silhouettes

These methods use a collection of parameters extracted from user binary silhouettes such as body size (height, upper body length, and thigh and leg length), step length, speed of step, and joint angles [8, 9]. These parameters are encoded with discriminant data and are slightly correlated together. These models of humans can be two-dimensional (2D) or three-dimensional (3D), relying on the number of cameras that record the walking from different angles. In [10], a method was proposed to extract the contour of the silhouette using periodic changes of joint angles as a model for classification. In [11], human walking was considered as a joint pendulum, and joint angles, hip height, and frequency of changes were recorded during the gait cycle. They mostly emphasized the lower half of the human body and the movement of the legs. And in [12] GaitSet assumed that the silhouette has included its position information thus regarded gait to extract temporal information.

2.1.2 Using A 3D Model

Recently, model-based methods have used 3D model parameters extracted from sequences. As reported in [13, 14], the images could be synthesized from the desired viewpoint by these parameters. In some articles, the path of limb movement and limb length were extracted as features [15]. Many researchers have optimized structural and dynamic models and proposed other feature extraction approaches to improve recognition accuracy. The researchers presented a three-dimensional model of video sequences made to show human walking, which is robust to items such as camera angle, clothing, and brightness [16]. In spite of this, these methods require a big video source and costly computing. They also did not test their methods in large databases. Depth digital cameras can be utilized to attain higher accuracy when using gait analysis and monitoring. The depth cameras retain more complete information in silhouettes while other methods fail to maintain the features of the top and bottom of the silhouettes. Most model-based approaches are used in high-quality sequences in a controlled environment and controlled angle variations. Considering these issues and due to sensor limitations and low video quality in model-based methods, these methods are not widely used in real environments and outdoors.

2.1.3 Extract Stable Features

Some model-based approaches extract and model features that do not change when the gait direction is changed. For example, in the method reported in the [17] the hip, knee, and ankle positions were extracted and modeled as features. In [18], the positions of the head and feet were used as features. These methods also have limitations. For example, gait recognition may be impaired if an obstacle blocks or masks the desired feature. On the other hand, in the case of the existence of a large change between testing and training sequences in the range of available walking directions these methods are ineffective.

2.2 Appearance-Based Methods

The spatial and temporal features that are used by appearance-based methods are obtained from observed gait sequences. These features are obtained without using 3D models and their parameters. The methods use silhouettes as an effective source for making gait patterns. Classification is done by computing the pixel-to-pixel difference and distance between the gallery and the probe.

2.2.1 Using the Gait Energy Image (GEI)

An appearance-based template is considered as the gait energy image (GEI). This method calculates the average silhouettes of a gait cycle and produces a gait template [4].

$$GEI\left(K\right)=\frac{1}{n}\sum_{t=1}^{n}I\left(t\right) \tag{1}$$

where I is an image of silhouette, t is the frame number, and n is the number of frames in the K-th gait cycle.

Since GEI converts spatial and temporal gait information into a single format, GEI-based methods typically have low storage requirements and low computational costs. On the other hand, using singular value decomposition, we can generate a transformation matrix that can transform GEIs obtained from a specified walking direction into another one. Subject recognition is based on exploring inter- and intra-user correlations. For example, in [19], the linear discriminant analysis (LDA) is used for this purpose, in [20], the multiple discriminant analysis (MDA), in [21-25], the convolutional neural networks, and in [26], the recognition was improved using Radon transform-based energy image. In [27], low-rank textures section of a walking texture image were optimized transforming any gait direction into a lateral gait direction. However, in the case of a wide range of changes, the recognition rate will be severely affected. On the other hand, apparent changes such as carrying a bag and changing clothes also affect the recognition rate. Researchers in [28] align various views GEI by the coupled bilinear discriminant projection (CBDP). In [29], in order to learn the properties that are robustness against angle, a MULTI-task Generative Adversarial Network (MGAN) is introduced. In this regard, in [30], a Discriminant Gait Generative Adversarial Network (DiGGAN) has been introduced, which uses it to extract immutable features.

2.2.2 Using the Entropy Image

Considering the challenges mentioned above, recognition could be done in two steps. The first step is recognizing the walking direction and the second is identifying the user in that direction. For example, in the method which is proposed in [31], recognition of the walking direction was carried out using the entropy from GEI's leg region. The user identification was also carried out by random subspace learning (RSL). The robustness of appearance changes was also improved by Gaussian filtering gradually highlighting the unaltered subject's shape.

2.2.3 Using the First and Last Frames and GTS

Some methods are presented in [32] to obtain the gait angle extracting the silhouettes of the subject in the first and last frames. Then, the gait angle was calculated using the two lines that connect the top-most and bottom-most points of the silhouettes. They also proposed the genetic template segmentation (GTS) which employs the genetic algorithm to automate the boundary selection process to improve robustness to appearance changes.

2.2.4 Using the PCA and LDA

In [31], a method was introduced that has two steps. This method distinguished the viewing angle from features by 2DPCA, then, to strengthen the robustness randomly used 2DPCA and then 2DLDA of subspace learning. In [33], the feet positions were analyzed in a GTI to recognize the gait direction. The user identification was also performed applying LDA for dissimilarity vectors that represent a user.

2.2.5 Using the PHash and Decomposition

In [7], a perceptual hash (PHash) was used to estimate the walking direction automatically. The PHash was computed over the leg region from the GEI. The GEI was decomposed into several sections and unaltered sections were selected by appearance changes to achieve robustness against appearance changes.

In this paper, a two-step method was proposed. The first step recognizes the walking direction and the second step identifies the subject. The first step, by combining five simple features of the leg region of the GEI, achieves an acceptable result over the other methods. These features are the maximum width of the leg region from the GEI, the ratio of the maximum width of the leg region of the GEI to the minimum width of that, the mean value of the center pixels of this region, the coordinate of the first pixel that has a nonzero value of the leg region from the left side, and the coordinate of the first pixel that has a nonzero value of the leg region from the right side. In the second step, a system is used for user identification. A novel method is used to decompose the GEI into several sections. The sections are N rectangular sections and equal size. The altered sections by appearance changes are masked. Data decorrelation and dimensionality reduction are carried out using the principal component analysis (PCA) and LDA. Since changes in appearance, resulting from changes in clothing or carrying a bag, usually involve a small section of the GEI, thus, the proposed method works well in identifying the subject.

3 The Proposed System

As shown in Fig. 2, the proposed system includes training and testing. In the proposed method, one of the most efficient and simplest walking shows, namely the gait energy image (GEI), has been used. This show is very economical in terms of time and computation due to its two-dimensionality. The interested user walking direction and GEI features are recorded in the database in the training phase. The database of walking direction includes five values of training of the leg region from

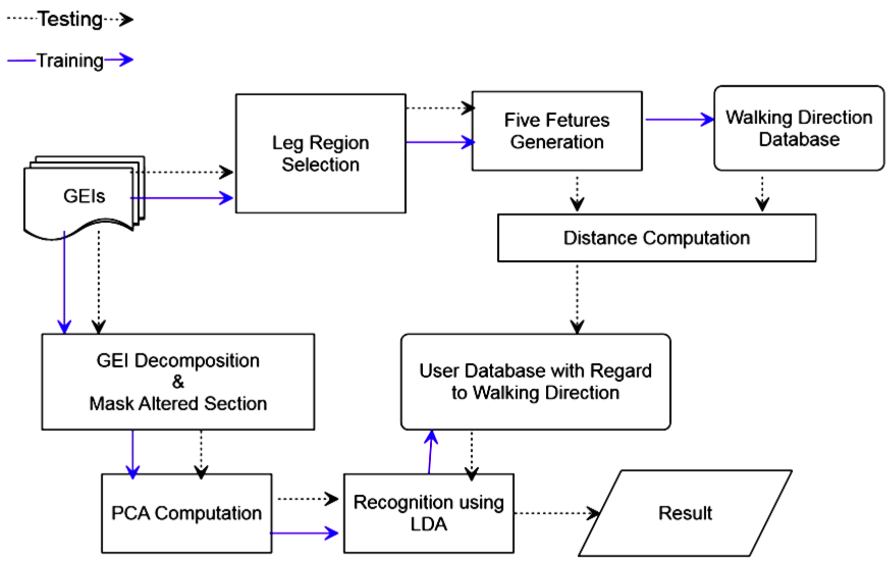

Fig. 2 Simplified flow of the proposed system.

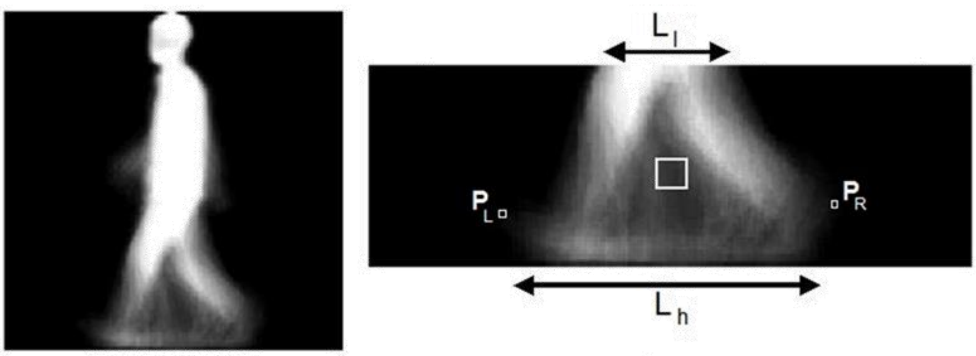

Fig. 3 Five values computed from the leg region of the GEI.

the GEI which is related to the considered walking directions. These values are the maximum width of the leg region from the GEI, the ratio of the maximum width of the leg region from the GEI to the minimum width of that, the mean value of the center pixels of this region, the coordinate of the first pixel that has a nonzero value of the leg region from the left side, and the coordinate of the first pixel that has a nonzero value of the leg region from the right side. A nonzero pixel does not mean that the pixel is really nonzero, but using a threshold, values greater than the threshold are considered nonzero. For each value, the distance is measured between the test and training using k-nearest neighbor (kNN) that is used for gait direction recognition. Then, the user gait direction is recognized by the adopted system based on the majority voting decision.

For each walking direction, the corresponding GEIs are grouped in the recognition step. Then, they are decomposed. The result is N rectangular sections of equal size. The same decomposing is carried out on the test GEI. The variance between the average of training GEIs and the test GEI is analyzed that is used to mask sections altered by appearance changes. Then, data decorrelation and dimensionality reduction are carried out by the principal component analysis (PCA) and LDA. In the end, the matching score is computed for user identification.

3.1 Recognition of Walking Direction

In [31, 33, 34], the training was done using the whole section of the leg region, however, the proposed method, for each considered walking direction, trains with the five values computed from the leg region of the GEI of all users. These values are as follows:

- The maximum width of the leg region from the GEI (L_h).
- The ratio of the maximum width of the leg region from the GEI to the minimum width of that (L_h/L_l).
- The mean value of the center pixels of this region.

$$m_p = \frac{\sum_{i=1}^{n} p_i}{n} \tag{2}$$

- The coordinate of the first pixel that has a nonzero value of the leg region from the left side (P_L).
- The coordinate of the first pixel that has a nonzero value of the leg region from the right side (P_R).

These values are shown in Fig. 3.

K-nearest neighbor (kNN) as the distance is used to recognize the walking direction. It is measured between the test and training for each of the five values. In the end, the majority of voting decisions are adopted by the system to recognize the user walking direction.

In this method, the leg region is not resized to a specific size (for example 32×32 pixels) because the overall shape of the GEI's leg region is affected by resizing. This causes misclassification among neighbor walking directions. Therefore, the resizing step is skipped.

The purposed method for walking direction recognition is very simple and understandable compared to other methods, so that after one training, little time and calculations are needed for walking direction recognition.

3.2 Identification of User

User identification is carried out when the recognition of the walking direction was completed. The test GEI is matched with the database comprising the training GEIs of to the recognized walking direction. Due to the changing of the features by walking direction changes, it isn't feasible to match GEIs obtained from different walking directions.

The GEI is decomposed into N equal size rectangular sections because by the splitting, carrying a bag or wearing a coat only changes a small section of the GEI and doesn't change the entire of it. Usually, poor identification results are attained in the presence of this small changed section. The decomposition limits the effect of changing the appearance to some of the sections. Therefore, the effect of appearance changes is eliminated masking these sections.

Then, similar to what was described in [7], PCA is applied to reduce each dimensionality of the GEIs. The principal components that have the highest variance are selected, and their projection are obtained onto the principal selected components. Then, LDA is applied for the data decorrelation of each GEI. A projection matrix is identified onto a subspace. Using Fisher's criterion, it maximizes the ratio of intra- to inter-class scatter. The intra-class scatter matrix $\sum_w$ and the inter-class scatter matrix $\sum_b$ for given n classes are given by (3) and (4), respectively.

$$\sum_w = \sum_{i=1}^{n} \sum_{x \in c_i} \left(x - \overline{x_i}\right)\left(x - \overline{x_i}\right)' \tag{3}$$

$$\sum_b = \sum_{i=1}^{n} m_i \left(\overline{x_i} - \overline{x}\right)\left(\overline{x_i} - \overline{x}\right)' \tag{4}$$

where $\overline{x}_i$ is the mean of the class c_i, $\overline{x}$ is the total mean, and m_i is the number of training samples for each class c_i.

The ratio of the between-class to the within-class scatter matrixes is maximizes by the transition matrix ϕ:

$$J(\phi) = \frac{\left|\phi^T \sum_b \phi\right|}{\left|\phi^T \sum_w \phi\right|} \tag{5}$$

Over a test GEI, the recognition is performed by decomposing it into N equal size rectangular sections. The system selects the unaltered sections in appearance changes. As shown in Fig. 4, for decomposing the GEI samples into N rectangular sections and choosing the unaltered sections, firstly, the test GEI is decomposed into M equal size horizontal sections. The horizontal sections that are changed in appearance changes are recognized. Then, the test GEI is decomposed into L equal size vertical sections and the vertical sections that are changed in appearance changes are recognized. Then, the intersection of these horizontal and vertical sections is masked on the test GEI. Compared to other methods, the proposed method retains more useful information. Useful information is information that has not changed with the appearance changes of the user and can still be used to identify the user. For example, in the method presented in [7], if the appearance changes are scattered vertically in the GEI, a large amount of the GEI will be masked and some useful information may be lost. However, in the proposed method, the altered sections are more carefully selected and masked.

The performance may be affected by the individual user's appearance. To address this issue, an average GEI is computed for all training sequences of each walking direction. Then, a threshold T is applied to recognize the changed sections in a test GEI. Similar to the method that is presented in [7], it is applied to the difference between the test GEI and the average image.

Finally, according to the following equation, Euclidean distance $d(,)$ is used to classify a test GEI z into one of the database classes:

$$\arg_k \min d\left(z\phi, \overline{x_k}\phi\right) \tag{6}$$

where $\overline{x}_k$ is the centroid for the k-th class.

4 Results

Dataset B of CASIA is the benchmark gait database that is used for experimental validation. The proposed method has widely experimented on the gait dataset B of CASIA. Institute of Automation of the Chinese Academy of Sciences collected it [35]. Gait silhouette sequences are contained in this database for 124 users. Each instance is captured over 11 view angles. As shown in Fig. 5 views range is considered from 0◦ to 180◦ with a step of 18° between adjacent views. In each angle, ten sequences are offered. Six sequences contain three pairs of sequences. They correspond to normal walking (N), wearing a coat (C), and carrying a bag (B).

Existing gait recognition methods are usually designed to work with personal computers and home

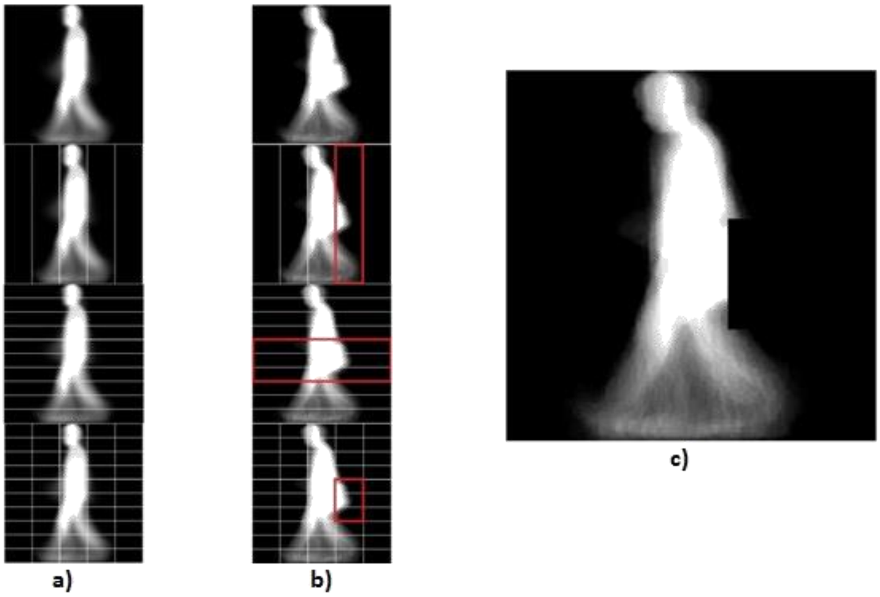

Fig. 4 An example of the proposed method of user identification. a) Decomposition of the average image into vertical and horizontal sections, and then, rectangular sections. b) Decomposition of the sample altered by carrying a bag into vertical and horizontal sections, and then, rectangular sections and identifying the altered sections by comparing it with part A. c) Masking the altered sections.

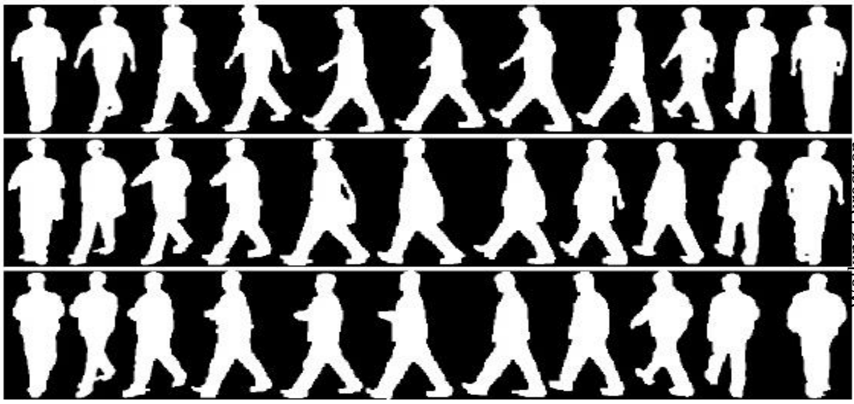

Fig. 5 CASIA gait database B. In 11 view angles and normal walking, carrying a bag and wearing a coat modes [35].

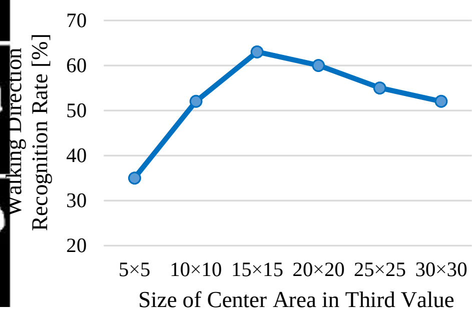

Fig. 6 Walking direction recognition rate to the size of the center area in the third value.

systems. The specifications of the hardware on which the proposed method is implemented are as follows: Processor: Intel Core i3-350M 2.26GHZ - 3MB Cache & RAM: 2GB DDR3.

4.1 Walking Direction Recognition Results

Similar to what was done in [7], the percentage of the leg region is 33% of the bottom of the GEI and the value of the parameter *k* is 6. The results of the experiments for the size of the center area in the third value are shown in the graph. As Fig. 6 shows, if the size is 15×15, the recognition rate will have the highest value for this feature.

In Table 1, the proposed method for recognizing walking direction is compared with the existing methods in [31, 33, 36, 7]. In the proposed method, similar to the entropy method [31], the training sequences were the first four normal sequences. The rest of the sequences, containing normal, coat, and bag sequences were used as testing sequences. In the method presented in [33] entitled improved entropy method, the first three normal sequences were used as training sequences. The remaining sequences were used as testing sequences. In the PHash method, the first four normal sequences were used as training sequences. The rest of them were used as testing sequences [7].

As mentioned, Table 1 shows the results of the recognition of walking direction. In this table, the methods are in columns. Each method has three sub-columns, the first, second, and third sub-columns correspond to the normal (N), the change of clothes (C), and carrying a bag (B), respectively. The rows in this table are the angles of walking directions that were considered at eleven different angles (with an interval of

Table 1 Correct walking direction recognition rate [%].

	Entropy method [31]			Improved entropy [33]			Contour method [34]			PHash method [7]			Capsule network (LBC & MMC) [39]			Proposed method		
View	N	C	B	N	C	B	N	C	B	N	C	B	N	C	B	N	C	B
0	83	80	79	89	79	89	98	96	98	99	98	97	83	61	72	99	96	97
18	94	87	85	98	84	92	99	99	99	99	97	96	89	68	78	98	97	97
36	88	85	80	89	79	85	98	98	98	97	96	92	87	65	75	99	98	95
54	92	90	89	98	95	95	99	99	98	98	98	93	91	65	78	98	96	95
72	81	80	78	90	89	88	98	99	98	99	97	98	89	67	79	97	97	98
90	89	79	72	86	69	73	97	97	97	94	92	90	89	65	78	98	94	94
108	79	75	70	85	64	69	95	94	95	98	98	96	93	66	79	97	98	97
126	90	88	85	93	83	89	98	99	99	99	98	98	85	68	80	99	97	98
144	83	81	79	85	73	82	96	96	96	96	95	93	91	66	79	97	96	95
162	89	86	84	88	88	85	97	96	99	97	94	93	91	70	80	98	95	94
180	82	80	75	88	86	76	99	97	99	99	99	98	88	65	73	99	98	97
Mean	86	82	78	89	80	83	97	97	97	98	97	95	89	66	77	98	97	96

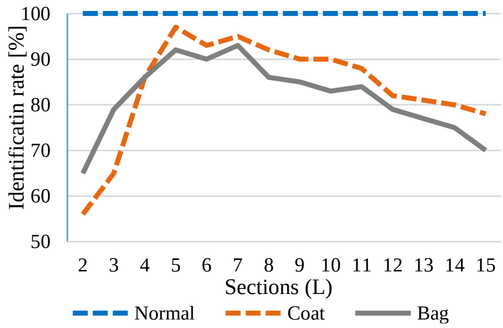

Fig. 7 The proposed decomposition method performance to the number of sections N.

Table 2 Correct rate percentage of user identification for lateral walking direction.

	N	C	B	Mean
Pal entropy method [37]	93	22	56	57
CCA method [34]	100	55	79	78
Weighting method [38]	97	78	91	88
Multiscale method [31]	100	76	89	88
GEI horizontal decomposition [7]	100	96	87	94
Attribute Discovery method [40]	99	86	90	92
Gabor filter bank+SRKDA [41]	98	87	92	92
U-Net [42]	98	53	85	78
GTS [32]	98	93	95	95
Proposed method	100	94	92	95

18 degrees). Examining the mean row, it could be concluded that the proposed method is almost more successful than the other methods. The contour and the PHash methods are also successful methods, but the contour method considers additional information to recognize the gait direction which is a limitation. On the other hand, the PHash method uses the intangible and incomprehensible features to recognize the gait direction while the proposed method uses a combination of five simple and comprehensible features. As mentioned, this feature is extracted from the leg region. Therefore, it makes the method robust to bags and coats alterations. Another advantage of this method over other methods is its simplicity and computational speed which makes it very understandable for ordinary people. For any method, simplicity and comprehensibility are considered as advantages if the results are acceptable.

4.2 User Identification Results

Since the proposed method should be comparable to other methods, this method is tested in the side view (90 degrees) in the CASIA database. The training sequences were the first four normal sequences. The remaining sequences including three pairs of normal, coat, and bag sequences were used as testing sequences. To decompose the GEI into N rectangular sections, firstly the GEI is decomposed into M equal size horizontal sections, and then, it is decomposed into L vertical sections of equal size. As reported in [7], the value of M was set to 11, and according to the experiments, the value of L was set to 5. On the other hand, because the first and last vertical sections don't include GEI, they have virtually no role in the identification. The results of the experiments for the number of vertical regions are shown in the graph. As Fig. 7 shows, the average Identification rate will have the highest value when the value is 5. Because if the value is 5, it optimizes both the conditions of carrying the bag and wearing the coat.

As shown in Table 2, the proposed method is efficient and acceptable compared to the best available methods. The average results of the proposed method are better than other methods. Most methods have good identification rates for normal sequences. The main challenge is appearance changes which drastically reduce the identification rate. These changes take place when the subject's clothing changes or the subject carries a bag. In both cases, the proposed method has relatively better results than the other methods. The proposed method is better than most methods in the case of change of clothes, and in the case of carrying a bag, it is better than all methods because the proposed method masks the altered sections and also tries to use all information of the unaltered sections for identification.

Table 3 Percentage of the rate of correct user identification.

	The proposed method of recognition of walking direction			Ideal walking direction		
Proposed method View [deg.]	N	C	B	N	C	B
0	98	82	86	100	85	91
18	99	85	86	100	85	90
36	99	87	90	99	89	90
54	98	91	92	99	95	92
72	99	94	89	100	96	90
90	100	96	91	100	92	91
108	99	91	90	100	89	90
126	99	87	90	100	91	92
144	100	89	89	99	91	90
162	98	83	88	99	85	87
180	99	80	83	100	89	86
Mean	99	88	89	100	90	90

Table 4 Comparison of mean correct user identification rate [%].

	N	C	B	Mean
Multiscale method [31]	99	69	87	85
RSL method [33]	99	38	77	71
GEI horizontal decomposition [7]	99	86	86	90
GEI with PGR [43]	97	84	75	85
GAITNET-pre [44]	94	63	82	80
GAITNET [45]	92	62	89	81
GAITSET [46]	95	70	87	84
HOG [47]	97	65	84	82
Proposed method	99	88	89	92

The results of the integration of these two methods are listed in Table 3. This table shows the result of identifying the subject in three modes: normal sequences, changing clothes, and carrying a bag. If you compare Table 3 with Table 1, you will find out that in some cases of the normal mode, the rate of the subject identification in Table 3 is higher than the rate of the recognition of the walking direction in Table 1. This means that the proposed system is robust to small gait direction misclassifications because although some walking directions were not recognized correctly, however, the subject was identified correctly. To make this point clearer, this method was tested in an ideal walking direction. The comparison of the results showed that there is not much difference in the results which means that the proposed system is robust to gait direction misclassification.

Finally, the proposed method was compared with the best available methods being robust to the appearance changes. The results are listed in Table 4. In this table, it can be seen that the results are acceptable in comparison to other methods in both the change of clothes and carrying a bag. The proposed method, compared to the PHash method [7], retains more useful sections for identification which is an advantage of the proposed method. In other methods, such as [41] and [7], sometimes the user's information is distorted in such a way that some useful information is lost, and sometimes many sections are deleted to delete the altered sections, which makes deleting more useful information.

5 Conclusion

This article presents a new method to identify the subject using gait. The method is robust to walking direction changes and appearance changes. For this purpose, the method is divided into two steps. In the first step, using five simple features in the leg region from the GEI, and then, using k-NN, the walking direction is recognized. These features are the maximum width of the leg region from the GEI, the ratio of the maximum width of the leg region from the GEI to the minimum width of that, the mean value of the center pixels of this region, the coordinate of the first pixel that has a nonzero value of the leg region from the left side, and the coordinate of the first pixel that has a nonzero value of the leg region from the right side. In the second step, the GEIs are decomposed into N equal size rectangular sections. By analyzing the dissimilarity between the training and test GEI’s average, sections altered are masked. Then, data decorrelation and dimensionality reduction are carried out by PCA and LDA. Finally, the matching score is computed for user identification. Masking altered sections and preserving most unaltered sections preserve more useful information. That's why it works better than other methods.

Simple classification methods including LDA and the gait GEI representation are used by the proposed system. Therefore, the user identification will be improved considering more complex classification tools in future work. Besides, the method of the recognition of the walking direction will be improved to tackle changes within a gait cycle. It could be done by more investigation of unaltered features by appearance changes. Therefore, it will reflect the user's walking direction better.

Intellectual Property

The authors confirm that they have given due consideration to the protection of intellectual property associated with this work and that there are no impediments to publication, including the timing of publication, with respect to intellectual property.

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A. Karizi: Conceptualization, Methodology, Software, Formal analysis, Writing - Original draft. **S. M. Razavi:** Supervision. **M. Taghipour-Gorjikolaie**: Investigation.

Declaration of Competing Interest

The authors hereby confirm that the submitted manuscript is an original work and has not been published so far, is not under consideration for publication by any other journal and will not be submitted to any other journal until the decision will be made by this journal. All authors have approved the manuscript and agree with its submission to "Iranian Journal of Electrical and Electronic Engineering".

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