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Human Recognition Improvement Using Fusion Of Gait And Facial Features

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Abstract

Biometrics are unique human traits that are stable over time. Face, iris, fingerprint and type of gait are biometrics used in identification systems. Face identification in distant images is one of the challenges that remains to be elucidated due to the lack of face detail, and efforts have been made to address it. One way to overcome this challenge is to use other biometricsbeside the face. In the fusion of biometrics, two or more biometrics are mainly used for identification and improving evaluation parameters. This paper attempts to solve the challenge of identification by fusion of the face and gait biometrics in decision level image fusion using distant images. This paper proposes a new method of identification using face and gait biometrics fusion. In the proposed method, the features of the facial images are extracted by means of the scale-invariant feature transform (SIFT) algorithm. Gait biometrics have been used to overcome the challenge of insufficient face image detail. To overcome the challenge of variations in the type of gait, the maximum curvature and histogram of oriented gradients algorithms have been used to extract the features. The obtained features are categorized using three classifiers namely, supporting vector machine (SVM), K-nearest neighbors and random forest in five stages; and finally by a decision level fusion rule, the identification is done. The proposed method is simulated on the ORL face database and the CASIA A gait type. The recognition rate of 99.50 and the precision of 99.80 indicate the superiority of the proposed method.

Keywords: Biometric, Gait Type, Face, Maximum Curvature, Histogram Of Oriented Gradients, Decision-Level Fusion.

1- Introduction

In terms of content

Identification systems, whose primary task is to identify the individual, are used to prevent people from accessing protected resources. Restrictions on non-biometric systems, such as degree of freedom restrictions, insecurity and password theft attacks, etc. encouraged researchers to turn to biometric systems for secure authentication and identification systems (Yousef, Khalil, Samra, & Ata, 2023). Generally speaking, identification technologies have the advantages of being unimaginable, unforgettable, inviolable, speed and ease of use of manpower and other advantages. Identifying a person with high confidence and precision has become a vital issue in many applications in the community, including computer, telecommunications and security networks. Biometric technologies are a proper response to strengthen the security shield against unauthorized access (Aryanmehr, Karimi, & Boroujeni, 2018). Among the large number of biometrics used in identification systems, face biometric is a relatively old and basic method (Zou et al., 2024). Given the age of this type of identification and the fact that facial images are still used as one of the common identification methods, it can be concluded that this biometric could be one of the most accurate biometrics available in image processing (Velesaca, Bastidas, Rouhani, & Sappa, 2024). Due to the importance and acceptable performance of the ID systems, many research, industrial and commercial investments have been made in this sector so far (Mehran Emadi, Karimi, & Davoudi, 2023). On the other hand, the process of identifying and recognition by gait and face is a fascinating topic in biometric researches today (Seyed Abolghasemi, Emadi, & Karimi, 2024).

Gait is a way of walking that can be used to identify people. Gait recognition in normal conditions is easy, but angle of view is an important factor because one has to walk the same path that is captured in the video images. The type of gait of each person is determined using some factors such as weight - length of foot and leg - type of shoes and gesture mode. Identification based on the type of gait is performed by extracting the silhouette images of the person gait by analyzing the images over time. Gait biometric is a criterion which is received from a person and is used to verify or identify individuals in life. Usually a biometric system attempts to extract patterns from one's behavior or physiological structure using pattern recognition algorithms and then stores these features in the database . Gait biometric is obtainable from distance and therefore does not require the participation of the person. On the other hand, since these images are obtained from a distance, they have poor quality, in other words, while the detail of the iris or even the face image are not clear from distance, this biometric is not highly efficient. For this reason, it has received much attention in criminology and surveillance processes (Rehman et al., 2022).

Image fusion is one of the branches of information integration that has received much attention in recent researches. Image fusion is done in three levels, including: 1- pixel-level fusion, 2- feature-level fusion, and 3- decision-level fusion (Rehman et al., 2023). At the Pixel-level fusion, which is at the lowest level of processing, raw images from a scene from different scales are combined to produce a new image that is more suited to human observation and interpretation and computer processing. Feature-level fusion, also called intermediate level fusion, extracts some of the features from the original images and then combines them into a general feature vector. This fusion requires the extraction of known objects in different sources using the segmentation process. Normal features such as edges, lines, corners, etc. are extracted from different images and merged by different methods. Decision-level fusion, also known as high-level fusion, provides a method in which it uses auxiliary information. This information is added to features extracted from source images. Information obtained through decision rules is examined to gain a better understanding of concepts and information and ultimately to make a final decision (Harouni, Karimi, Nasr, Mahmoudi, & Arab Najafabadi, 2022).

Each of the biometric recognition and identification methods has it's pros and cons that combining with other security methods can eliminate existing weaknesses. Today, identifying individuals' identity in information transport is a vital element in data security. Therefore, there are various ways to identify people. These methods are used not only to secure computer systems but also to increase the security of companies and locations. Nowadays, the use of biometrics in identifying or verifying people's identities in a fusion way, is a common practice in the field of security in places such as universities, airports, ministries and even computer networks. As such, fusion of biometric systems offsets higher costs by providing better performance [5].

Face authentication is difficult especially in distant images, because image details are lost, and as a result, identifcation is difficult. To overcome this problem, improving image recording and insertion hardware can be useful, which is an expensive solution. Another solution seems to be to use other biometrics besides face biometrics. One of the most prominent biometrics along with the face is gait biometric. By combining these two biometrics, the recognition rate, precision, or other parameters can be improved. The main purpose of this paper is to improve the identification of individuals using facial and gait features fusion (Harouni, Karimi, & Rafieipour, 2021). For this end, identification is performed using two models of identification by means of two biometrics including face and gait. Face identification is done through feature extraction descriptor with scale-invariant feature transform (SIFT) algorithm and gait identification is based on the average individual silhouette images on different gait periods using the maximum curvature and histogram of oriented gradients algorithms. The extracted features are categorized into five phases by the three classifier and finally identified by decision-level fusion (Seretis & Sarris, 2021).

SIFT is one of the most widely used descriptors with high consistency against changes such as rotation, zoom, image elongation and lighting. This method works on the basis of the feature extracted points on the image. Today, this descriptor is one of the best and most powerful tools for extracting non-sensitive key points under various conditions such as rotation, zoom, shift, noise, lighting and elongation conversion. In general, the steps of using this descriptor can be divided into three main parts. In this paper, we have tried to overcome problems such as rotation by using this descriptor (M. Karimi, Harouni, Nasr, & Tavakoli, 2021).

The maximum curvature descriptor is a key component of the feature extraction step(Khan et al., 2021). The whole curvature process is divided into three stages: extracting central positions at the edges, increasing sensitivity, and attaching the central point to improve the edges. To extract the central positions of the edges, first the cross-sectional profile analysis is applied to the image and then the local maxima are calculated in the cross-sectional profile. To further explain this method, if the value of $F(x,y)$ is the brightness of (x,y) pixels, then $P_f(z)$ is a cross-sectional profile which is obtained of $F(x,y)$. This algorithm is convoluted as a line on the image at different angles. Then, according to the brightness of the image, the graph for each column of the pixels is plotted (M. Karimi, Harouni, Jazi, Nasr, & Azizi, 2022).

$$G_x = I \star D_x$$
$$G_y = I \star D_y \qquad (1)$$

In equation (1), I is the main image, D_x and D_y are sobel kernels in the x and y directions and $\star$ operator represents the convolution. In the second step, size and orientation of the gradient in each pixel is calculated for three color spaces of (B.G.R) and the maximum value is chosen as the gradient size of that pixel, the gradient of each pixel is obtained by equation (2) (M. Karimi, Harouni, & Rafieipour, 2021).

$$|G(i.j)| = \sqrt{(G_x(i.j))^2 + (G_y(i.j))^2} \qquad (2)$$
$$\theta_G(i.j) = \tan^{-1}\frac{G_x(i.j)}{G_y(i.j)}$$

Where, the absolute magnitude of G is the gradient size, θ_G is the gradient orientation, and i and j represent the number of rows and columns, respectively. In the third step, a 1*1 pixel cell is considered and in 3 bins, the histogram of the cell is calculated. Each block consists of four cells, and each block contains a histogram with a maximum of 31 bins, which is normalized using the normalization method (Navabifar & Emadi, 2022).

In general, the information fusion refers to the combination of different information in order to achieve better quality, depending on the intended application. The word "different" has a vast meaning in the above definition. The most remarkable and precise integration of the information of various sensors takes place in human mind. The five senses of the human (vision, touch, hearing, smell, and taste) receive different information about a subject. This information is processed in the brain and ultimately is integrated to form the person's decision. Image fusion is one of the branches of information fusion that has received much attention in recent researches (E. Karimi & Ebrahimi, 2016). At the Pixel-level fusion, which is at the lowest level of processing, raw images from a scene from different scales are combined to produce a new image that is more suited to human observation and interpretation and computer processing. Feature-level fusion, also called intermediate level fusion, extracts some of the features from the original images and then combines them into a general feature vector. This fusion requires the extraction of known objects in different sources using the segmentation process. Normal features such as edges, lines, corners, etc. are extracted from different images and merged by different methods. Decision-level fusion, also known as high-level fusion, provides a method in which it uses auxiliary information. This information is added to features extracted from source images. Information obtained through decision rules is examined to gain a better understanding of concepts and information and ultimately to make a final decision. This level is the highest level of fusion and the decisions which are made, are integrated on the basis of every single resources at this level and final decisions are made (Raftarai, Mahounaki, Harouni, Karimi, & Olghoran, 2021).

The main idea of this paper is based on the principle that, since the features of the face distant images are not sufficiently identifiable, one can use the combination of one's gait style in this issue which can be the innovation of this article. This article is further divided into the following sections. Section 2 presents the research background. Section 3 presents the proposed method. Section 4 concludes and discusses the proposed method in full. Finally, Section 5 summarizes the results of the whole article.

1. LITERATURE REVIEW

In (Mobarakeh & Emadi, 2022), two strategies of (GMTR), (GPTR), have been presented, and tested on the ORL, yale and FERET databases, with the highest value of 93.67 for the ORL database. However, it should be noted that all three mentioned databases are without specific position and these values are insignificant for these databases.

Farrokhi et al (Farokhi, Sheikh, Flusser, & Yang, 2015) in a paper entitled "Near infrared face recognition using Zernike moments and Hermite kernels", proposed a new method of identity identification. In this paper, images are extracted in two local and global phases of the feature and are produced by combining the features extracted in the feature vectors of each image. To identify each image in this method, the feature image vector is generated by the mentioned method. This vector is then compared with the database image feature vector under the equation presented in the article and the image whose feature vector is most similar, is identified as the target image. The method of Farrokhi et al. is done with the precision of 87%, but the critical point that can be made in this article is that more challenges can be evaluated, which these challenges are evaluated in the proposed method (Sultan & Faris Ghanim, 2020).

In (Gao, Zhang, Zhao, & Zhang, 2024) in an article titled "Multilayer lighting detection for identity identification ", overviewed all studies in this regards. In this article, the researchers have examined and compared all the preprocessing, extraction of features and categories in light challenge research. The only downside of this review article is that it deals with only one challenge, but the strength of this, is that it is almost a comprehensive research on the light challenge and can be a good guide for exploring ideas in other challenges (Wu, Xin, Fang, Hu, & Hu, 2019).

In (Iranpour Mobarakeh & Emadi, 2020) , presented a novel approach for identity identification in an article entitled "Implementing discrete wavelet and discrete cosine transform with radial basis function neural network in facial image recognition". In this paper, 131 images of 41 students were used and discrete cosine transform and discrete wavelet transform were applied to them, and the detection process was performed using radial basis function neural networks. The test results show that the best values for the radial function are 41 * 41 * 8 and the recognition rate in this paper is 98% which is acceptable.

In (Majid Emadi & Emadi, 2020) introduced a new dimension of light challenge to face identification through face images. In this paper, to obtain discrete information from image reconstruction errors, both linear coefficient and 1-minimalzation reconstruction error are constrained and then calculated using similar transformations of parameters in a linear system. Although the results are not good, the important point is that this research can sometimes be considered as a starting point for research with different challenges.

In (Qiao, 2021) presented a new approach to face recognition using a combination of Gabor extractors and Zernic mines. In this paper, first 40 sub-images of the original images were produced with 5 scales and 8 Oriantations, using Gabor filter. Then, from each sub-image, ۴ Zernic properties are extracted and the results are categorized by the nearest neighbor method. The recognition rate in this paper was 89.23%, which is not acceptable. However, in the database produced by the research team, the recognition rate reached 98.5% [8].

In (Nakajima, Mitsugami, & Yagi, 2013) presented a new approach for identifying faces with different facial images using the convolutional neural network. The images used in this paper were captured in different angles to explore a new challenge in identifying faces using face images. In this research, two modules of identification and control are used. The feature extraction is performed in the GNG-VGG module and classified by the nearest neighbor classifier. The results of identity identification at different angles (90 ° to -90 °) show that only at zero degree, the precision is 100% and in other angles, precision is in its minimum level. Nevertheless, it should be noted that even at high angles, such as 90 degrees, results are acceptable.

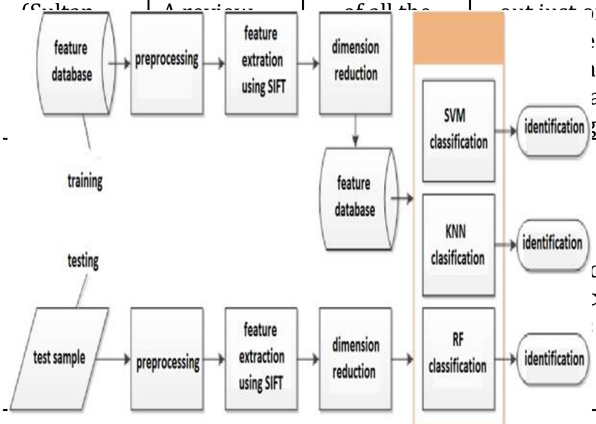
In (Vinay et al., 2016) proposed a face detection method using the EOH-SIFT filter. This paper presents a method for implementing face recognition using filtering methods. The use of filtering increases the precision of this process and also recognizes faces with greater certainty. The proven process is stable against rotational scaling and image brightness. The idea of doing this paper is taken from the EOH-SIFT approach in this paper. It intends to improve the impact of EOH-SIFT . To do so, it provides a filtered image as an input to EOH-SIFT. In this paper, the ability of the

EOH-SIFT approach in face recognition is greatly enhanced by the use of two filters that operate in a particular order. Testing this approach on the ORL database has yielded very promising results. Face detection first starts with finding the areas of interest and then applying filters to those areas. Finally, using an efficient nearest neighbor algorithm, the features of the faces and filtered areas are matched, creating a robust face recognition system.

For further evaluation, these methods are compared in Table 1 and the disadvantages and advantages of each are shown.

Table 1. Comparison of previous methods and their disadvantages and advantages.

Author Name	suggested method	Advantages	Disadvantages
(Sultan & Faris Ghanim, 2020) Li Yu et al. [16]	features Gabor texture and general and gamma Gaussian model	Investigating the methods presented on several databases and proposing two efficient algorithms for identification	Failure to explore different challenges in face recognition
(Wu et al., 2019)	Combining the features of the Zernik moments and the Hermit filter in infrared facial images	Increasing efficiency and quick identification with removing the classifier, ward presents a new method in the classifying of	Failure to explore different challenges in face recognition
(Sultan ...	A review ...	A review of all the ...	Checks out just one ... e of ... t ... ace ... ge
			... d to ... cific
(Qiao, 2021)	A combination of Gabor extractors and Zernik moments for face recognition	Poor results in identification	Introducing new and improved methods of identification
(Nakajima et al., 2013)	Identification with facial images using convolution neural network	Low face recognition rate in the experimental database	Generating a database and providing a high-efficiency method for identification
Hu et [19] al.	To obtain discrete information from image reconstruction errors both linear coefficient and reconstruction error with1-minimalzation	Identification with the spin challenge with strong results	Angular image review regardless of the intrinsic challenges of the face



1. THE PROPOSED METHOD

The main purpose of this paper is to propose a new method of face identification by fusion by gait biometrics, which is based on decision-level fusion derived from two biometrics. For this purpose, the identity recognition rate of two biometrics will be calculated. In the proposed method for face images, scale-invariant feature transform (SIFT) descriptor is used to extract robust features. Obtained feature vectors are classified using three classifiers, SVM, K-nearest neighbors and random forest. In gait biometric, after extracting the silhouette binaries images, in order to find robust image features, the maximum curvature algorithm and the histogram of oriented gradient will be used. The vectors and matrices obtained in the silhouette binary images are classified using two classifiers; SVM and K-nearest neighbors. In the end, the results of the feature classification are merged with the help of an appropriate fusion law to obtain the best result.

1.1. Block Diagram of the Proposed Method

Identification from face images is one of the best and oldest methods of identification. Each identity identification process is divided into two major parts of test and train. Commonly in an identification process, in the train phase, there are pre-processing, feature extraction, feature selection and classification stages. In the test phase, in addition to the stages of train phase, there is an evaluation phase. Fig. 1 shows a block diagram of the proposed method of face recognition.

This article uses the ORL images database. Database of ORL face images contains 120 images corresponding to 40 persons. There are 5 images per person in this database, 3 of which are used in the training process and 2 images in the test phase.

Feature extraction is done using SIFT and selecting the appropriate points for authentication. Selection of points robust to size and rotation, selection of key points in place, orientation of each point, and generating local and global descriptors are some of the benefits of features selected by SIFT.

Fig. 1. Block diagram of the proposed method for identification using face biometric during the training and testing phase.

After extracting the feature and selecting the best one based on principal component analysis, classification of feature vectors is done in the form of features matrix. In this paper, three well-known classifiers; SVM and KNN and RF are used. The SVM classifier has several windows in which RBF windows are used in this paper for evaluation. In KNN classifier, metric and neighborhood radius are addressed and three criteria; cosine distance, Euclidian distance and Mahalanobis distance are tested in 1 and 3 radii. In the RBF classifier, each decision tree is normally a binary tree, and data is propagated between each tree starting from the root of the tree. At each node, the data is subdivided into f (x) <τ using binary tests, where f and τ are provided by the training data. Classification results are used for fusion. In the classification process, 70% of the data is used for training and 30% for testing. It should be noted that the classification process, and the instruction of clusters, take place after the feature selection.

۳.۲ Identification Using Gait Biometric

Identification methods in gait biometrics are classified into two groups.

Model-based approaches

Model-free methods

Model-based methods consider the geometrical structure of the human body as the main model and then extract the relevant features of the human body for authentication. Generally speaking, identification using gait biometric in online scenario is very challenging. In fact, the way people walk depends largely on one's mental or physical condition. In model-free methods, binary images are typically extracted from video frame sequences called silhouettes. Most of these methods have one common disadvantage. Inter-class changes caused by walking such as carrying a bag, changing clothes, and even changing body angles have a negative impact on final identification. In this paper, a new method based on the local maxima of the histogram of oriented gradient is used. Fig. 2 shows the block diagram of the proposed method of identification using gait biometric in the training and testing phases. The feature vectors are classified using the three classifiers mentioned above

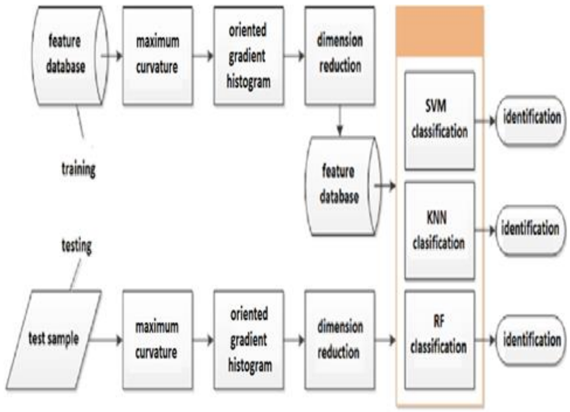


Fig. 2. Block diagram of the proposed method for identification using gait biometric during the training and testing phase

Despite efforts to improve the recognition rate, due to the challenges facing feature extraction such as the dependence of one's movement on mental and physiological states, extracting the appropriate feature from binary silhouette images is challenging. In this article, a new method will be used with the help of geometric methods to extract the property. The maximum curvature method is one of the most successful methods used to extract feature from the image in other biometrics such as, palm blood vessels. The maximum curvature method [19] identifies the small curves in silhouette images. It should be noted that this descriptor could easily identify changes when body postures and body structure change.

۳.۳ Decision-Level Fusion

Fusion laws are used at the decision level to merge the image. The most common rules used for image fusion are the selection of maximums, minimums, and then averages. It seems that the law of maxims is the most common law in decision making. The block diagram in Fig. 3 illustrates the decision-level fusion process proposed in this paper.

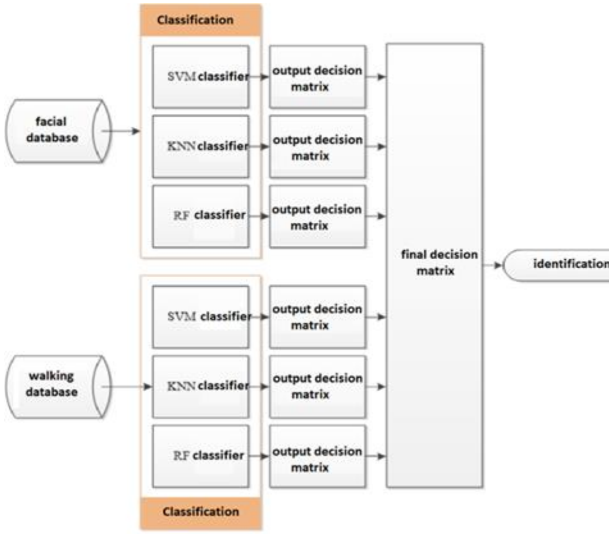


Fig. 3. Block diagram of the proposed fusion process

Each of the classifiers used in the biometrics in question produces an output matrix whose dimensions are 40 x 1. That is, rows stand for the number of people. Since, three classifiers are used in five modes, the final decision matrix has dimensions of 5 x 40. In each row of output, the value with maximum repetition will be considered as the final result. For example, it is expected that in line 37, the numbers of [37 37 37 37 37] are available. It means that all classifiers have identified the person to be the No. 37 from the database. Now if other numbers are recorded, the number that has the most repeat will be considered as the final exit and decision.

1. RESULTS EVALUATION

This paper presents a novel approach based on the fusion of face and gait biometrics. In the proposed method, the appropriate features for identifying are extracted from the face and gait biometrics, then they are classified by the proposed classifiers and finally categorized by a proper fusion law called majority voting. Precision rate and recall rate criteria were also used to evaluate the proposed method. Processing time and recognition rate are also considered as a side criterion.

$$Recognition\ Rate = \frac{P}{T} \times 100 \qquad (۳)$$

In equation (3), P represents the correctly identified images and T represents the number of all images. Moreover, the precision rate and recall rate of the proposed method in this paper will be calculated based on equation (4) and (5), respectively.

$$\Pr ecision = \frac{TP}{TP + FP} \qquad (۴)$$

$$\textbf{recall} = \frac{TP}{TP + FN} \qquad (۵)$$

Where, TP represents true positive and FP is false positive.

The simulation of the proposed method is performed by MATLAB R2017a on Windows 10 operating system and the hardware platform used to simulate this research is an Intel® Core ™ i5-8500 system with 8 GB of RAM, plus 16 GB of RAM reserved from the SSD hard drive. In the proposed method, the necessary features from the face are extracted by the SIFT extractor and the maximum curvature algorithm as well as the histogram of oriented gradient are used for the required features from the silhouette images. Then, using the principal components analysis, the feature selection and dimension reduction are performed. By means of the RF, SVM and KNN classifiers, data are classified. A feature vector is extracted from each classifier, and finally, authentication is done by the fusion law of majority voting. The proposed approach has been compared with the methods available in the single classifiers. The results show the superiority of the proposed method. Fig. 4 illustrates the comparison of the proposed method with single classifiers in face biometrics at the recognition rate criterion. This chart illustrates the superiority and precision of the proposed method in the best possible way. This is because of the use of image fusion at the decision level. Fig. 5 illustrates the comparison of the proposed method with other single classifiers in face biometrics in terms of precision. As shown in the graph, the results show that the proposed method has achieved better results in integration. Fig. 6 shows a comparison of the recall rate of the proposed method in single-face biometrics. The results of this graph show the superiority of the proposed method. Fig. 7 shows that the proposed method takes more time to execute. Of course, this disadvantage can be ignored against its brilliant results. Combining classifiers with a proper integration law has produced superior results.

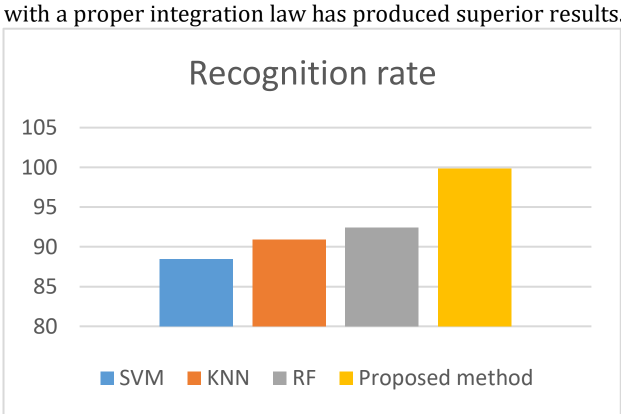


Fig. 4. Comparison of the recognition rate of the proposed method and other single classifiers in face biometric.

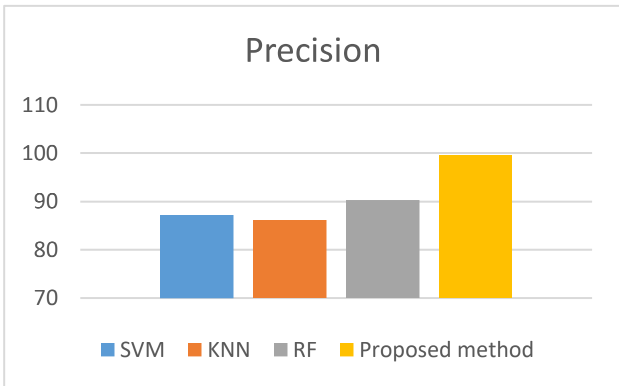


Fig. 5. Comparison of the precision of the proposed method and other single classifiers in face biometric.

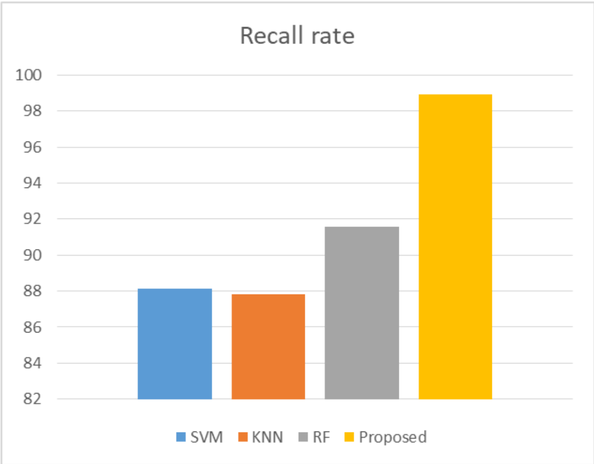


Fig. 6. Comparison of the recall rate of the proposed method and other single classifiers in face biometric

Fig. 7. Comparison of the recognition time of the proposed method and other single classifiers in face biometric.

Figs. 8 to 11 illustrate the comparison of the proposed method with the single classifiers in the single-gait biometrics in terms of the recognition rate, precision, recall rate and recognition time, respectively. These graphs show the superiority of the proposed method as best as possible in the precision and recognition rate criteria. The combination of the two biometrics in a seamless integration has been able to overcome the weaknesses of the single classifiers and improve the identity recognition results of the two biometrics. Fig. 8 shows the comparison of the proposed method recognition rate compared to the single classifiers. As the diagram shows, the proposed method has achieved the best results with the highest recognition rate of 99/50. Fig. 9 also shows the comparison of the precision of the proposed method in recognition. As the diagram shows, the proposed method has the best precision of 99/87. Fig. 10 presents the comparison of the recall rate of the proposed method to other single classifiers for identifying the gait biometric. As shown in Fig. 10, the proposed method achieved the best results. Fig. 11 shows a comparison of the time of evaluation and recognition in this biometrics, which shows that the proposed method takes longer to run. Of course, this disadvantage can be ignored against its brilliant results.

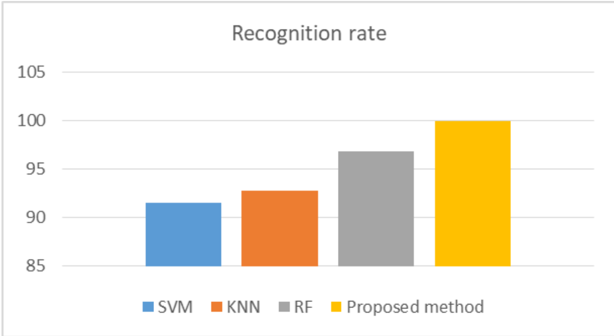


Fig. 8. Comparison of the recognition rate of the proposed method and other single classifiers in gait biometric

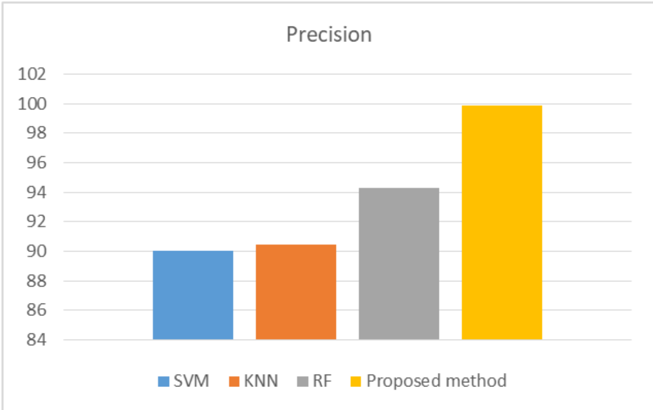


Fig. 9. Comparison of the precision of the proposed method and other single classifiers in gait biometric

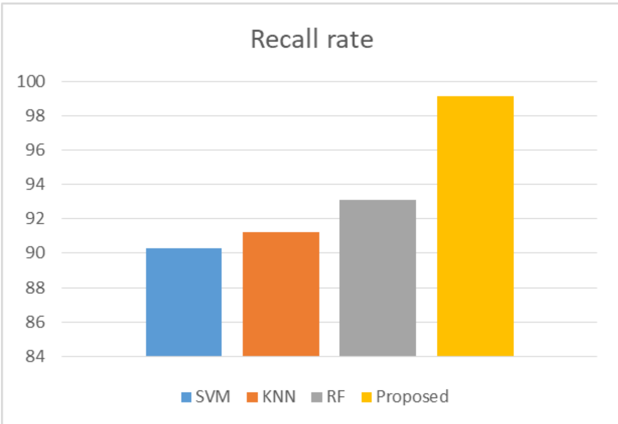


Fig. 10. Comparison of the recall rate of the proposed method and other single classifiers in gait biometric.

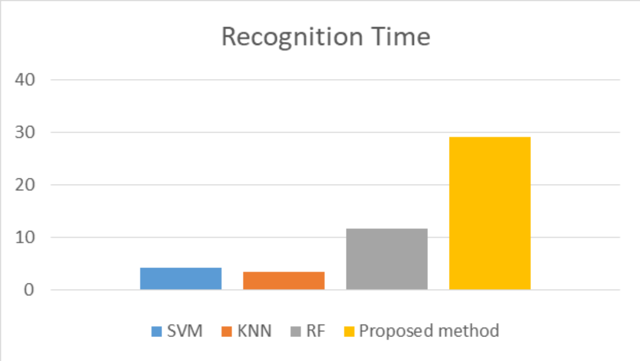


Fig. 11 Comparison of the recognition time of the proposed method and other single classifiers in gait biometric.

In order to have further evaluation, the proposed method, this method is compared with the methods presented in [24] and [25]. Since only the recognition rate was compared in these articles, this comparison was made from the recognition rate perspective. Fig. 12 illustrate these results. The advantage of the proposed method in this matter is also evident. The superiority of the proposed method is due to the use of appropriate features, efficient classifiers and the proper fusion law.

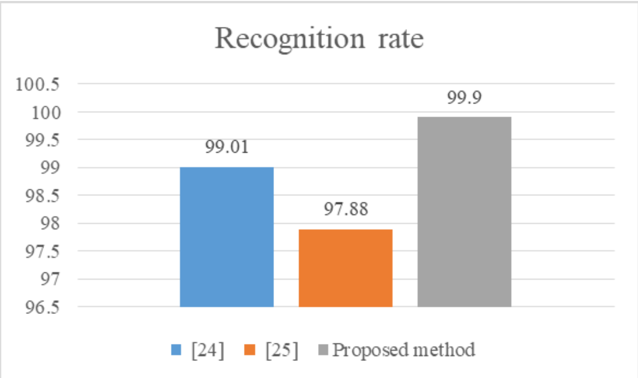


Fig. 12 Comparison of the recognition rate of the proposed method and methods of [24] and [25]

1. CONCLUSION

This paper proposes a new method for human identification using fusion of face and gait biometrics. The proposed decision-level fusion method reviews the decisions taken by the applied classifiers using the majority voting fuison law and announces the final outcome, which is the identity of the person in question. The proposed method was compared in terms of recognition rate, precision and time criteria with single classifiiers and single biometrics system. The recognition rate of 99.50 and the precision of 99.99 against the poor results of these single biometrics indicate the superiority of the proposed method. For further evaluation, the proposed method was compared with [24] and [25] in the recognition rate criterion. Still, the proposed method proved its superiority. In terms of the time criterion, the proposed method requires more time to perform identity identification because of having more steps than the single biometric methods. Proposed method includes two parallel phases of feature extraction and identification using classifiers and then, decision level image fusion, which in turn leads to more time. Of course, given the brilliant results, one can overlook this disadvantage

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