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A WIRELESS MULTI-ACCESS SECURITY SYSTEM USING REAL-TIME FACE RECOGNITION TECHNIQUE

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Abstract

The security systems have been widely used in many applications, where the trend nowadays is to build such systems that are characterized by accuracy, high speed and low complexity. This work proposes an access control system with multi-entrance using the process of identifying human faces, where the system comprises two access nodes and a control unit. The features of detected faces at each node are wirelessly sent to the control unit for verification. The proposed face recognition method investigates the aim of data reduction and fast classification. The facial features are extracted using a multi-level discrete wavelet transform, which in turn achieves the first reduction in the manipulated data. The second stage of data reduction is implemented by calculating the mean of training images for each individual to construct one training vector instead of using multi-vector array. For identification, the similarities between the probe and global images are computed using Euclidean distance. The simulation results of the proposed face recognition method reach the best accuracy rates, whereas the real-time recognition achieves an accuracy of about 91.46 %.

Keywords: Access control, Discrete wavelet transform, Face detection, Face recognition, Feature extraction, TCP/IP, Wireless communications.

1. Introduction

The biometric recognition has been used in many disciplines, such as access control, authentication and surveillance. Due to its widespread utilization, face recognition (FR) technique has become more applicable over other biometric branches such as fingerprint, palmprint, iris and speech. This technique is widely used in airports, criminal identification, employee attendance, and other applications, such that the face image is frequently captured without informing the people. The earlier FR methods used the geometric matching that consumes large memory and time, but recently, the template matching has been used due to its advantages in reducing the processing data [1]. Several methods have been demonstrated relating to data reduction, which in turn achieve a reduction in the computational complexities. Discrete Fourier transform (DFT) [2], discrete wavelet transform (DWT) [3], discrete cosine transform (DCT) [4], Karhunen-Loeve transform [5], fisher-face [6], singular value decomposition [7], and local binary pattern (LBP) [8] are the most techniques used for complexity reduction. Several algorithms have been proposed to train and test face images such as support vector machine (SVM) [9], k-nearest neighbour (KNN) [10], neural network [11], elastic matching [12], and hidden Markov model (HMM) [13].

DWT is an excellent feature extractor and data compressor that decomposes the image into approximation and detailed coefficients. The useful features are included in low-frequency coefficients, i.e. approximation coefficients, whereas the detailed coefficients involve high-frequency coefficients such as illuminations and noise. Therefore, the high-frequency coefficients may be neglected, and only the low-frequency coefficients can be used to describe the facial features with reduced image size. For more reduction in image size, the approximation coefficients of each stage are decomposed until reaching the desired level of DWT.

In this work, facial features are extracted using different levels of DWT, such that the number of levels is determined according to the image size and the accuracy rate. In the recognition section, Euclidean distance is used as a classifier, and the experimental results are discussed for verification.

The remaining sections are outlined as follows: Section 2 presents a brief explanation for the related approaches. In Section 3, a background for the DWT is provided. An illustration of the proposed FR scheme is introduced in Section 4. Section 5 presents the simulation results, comparisons with the related FR approaches, and the implementation of a multi-access control system. Finally, the essential topics of the proposed work are concluded in Section 6.

2. Related Work

In the literature, the researchers enrich the FR field by different methods that comprise various features representation, training algorithms, and classifiers. The related approaches are chosen according to their use of wavelet transform (WT) due to its importance in this work. A comparative study was introduced in [14] between DWT, Gabor wavelets, and principal component analysis (PCA). The study concluded that the performance of Gabor wavelets is optimal, but DWT is better than PCA in spite of its minimal processing time.

In [15], a supervised method was used to extract and classify facial features, which is called locally discriminating projection. Two levels of DWT were applied to each face image, and the inverse of DWT was used for image reconstruction by suppressing or discarding some coefficients. The work achieved a better recognition rate than the use of Eigen-faces and Laplacian-faces. However, it used all the sub-bands of DWT that require a large memory size in addition to the use of a reconstruction process, which is not suitable for real-time processing due to the additional time consumption.

Dual-tree complex wavelet transform (DT-CWT) was used in [16], and the experiments verified that this technique is more accurate than other methods such as DWT and Gabor wavelet transform. Although a useful feature representation was used, the size of the input image was initially extended, which added extra complexity to the algorithm. Furthermore, some sub-bands were selected using a hard threshold comparison, which achieved a low recognition rate due to discarding some critical facial features.

In [17], three transformation methods were examined for features representation; DWT, DFT and DCT. The best results were obtained from using a spectrum face that is a fusion of DWT and DFT, and the Euclidean distance. The use of one level of DWT requires more memory and time than the use of multi-level DWT. Besides, more complexity was added to the system because of using DWT with DFT, where the use of only DWT is sufficient to reach the goal.

A fusion of Radon and DWT was used in [18] for feature extraction, and the classifier was the nearest neighbour method. Initially, Radon transform was used to extract features of different orientations, and also to eliminate noise. Then, three levels of DWT were applied, were the lowest frequency band was chosen to represent the face features. Although the method satisfies the highest recognition rate, it comprises two transformation methods, Radon and DWT, which increase the size of utilized memory and processing time.

In [19], Haar wavelet was used to improve the quality of face images by normalizing the DWT coefficients. The City-Block distance was used as a classifier, such that the distances between the test image and training images are calculated. The normalization process was applied to the images that their global light qualities are less than a predefined threshold value. The suggested method is useful for detecting the variations of illumination in the tested images. However, it cannot detect the variations in the posture of real-time images.

DT-CWT, including a local fusion of coefficients, was used in [20] for extracting features, and the classifier was Euclidean distance. The experiments appeared the superiority of this technique over the traditional DT-CWT and Gabor wavelet methods in term of recognition rate. However, it requires intensive processing time as well as it cannot tackle the problem of light intensity variations in images. In [21], the histogram of LBP and the generalized neural network were used with Gabor wavelets in both feature extraction and classification methods, respectively. In the classification part, the wavelet was used as an activation function of the neural network. The method is robust to a slight variation in pose and imaging conditions. However, the main drawback is the processing complexity that prevents the method from meeting the real-time requirements.

A hybrid FR system was introduced in [22] using Haar wavelet and PCA or linear discriminant analysis (LDA), where all sub-bands of a specified level of DWT were used. The db1 and db4 wavelets were separately used for image decomposition, whereas the nearest neighbour and SVM were used for image classification. As illustrated previously, the use of whole sub-bands of DWT requires more memory and time than the use of a low-frequency sub-band only. Also, the purpose of using PCA or LDA was to reduce the processing data but, at the same time, it consumes extra processing time.

In [23], a combination of LDA and adaptive directional WT was used for extracting features, and Euclidean distance was used for classification. A prediction filter was used to extract the necessary coefficients of the lowest frequency sub-band. Although the filter reduces the size of processing data, the processing time was increased due to the use of adaptive directional WT and LDA stages.

A new strategy has been proposed in [24], which is implemented by applying five levels of DWT to each face image using five different types of wavelet instead of using the same type for all levels. PCA is used in conjunction with DWT to extract features and to reduce their size, whereas Euclidean distance is used as a classifier. As the wavelet functions have different shapes and complexities, the use of multi-wavelet functions increases the computational complexity. Furthermore, the size of processing data can be reduced in the case of using the PCA algorithm, but at the same time, the processing time is increased.

In [25], the FR system is constructed using four levels of DWT and HMM, such that the db1 wavelet was used in the image decomposition. The lowest frequency coefficients are segmented into overlapped blocks. Then, the mean (μ) and covariance (Σ) of the extracted blocks are calculated and processed using HMM to form a training model for each individual. Although this method achieves 100% accuracy rate, it requires a large memory size because of using a segmentation method that is followed by the construction of two matrices, μ and Σ.

A combination of a histogram, DWT, fuzzy logic, DCT, and PCA is used in [26] to extract features from face images, which are classified using the KNN algorithm. Using a multi-stage feature extraction process highly increases the complexity of the system. Besides, the DCT is applied to whole image histogram and each block of DWT's sub-images, and also the inverse of DCT is used after the fuzzy filter step, where this process wastes more processing time.

In [27], the facial features are extracted using the detection of facial parts, DWT, and vector quantization algorithm, whereas the Euclidean distance is used for recognition. It is difficult to understand the importance of using three methods of features extraction while the DWT is sufficient for this purpose, as it will be seen later.

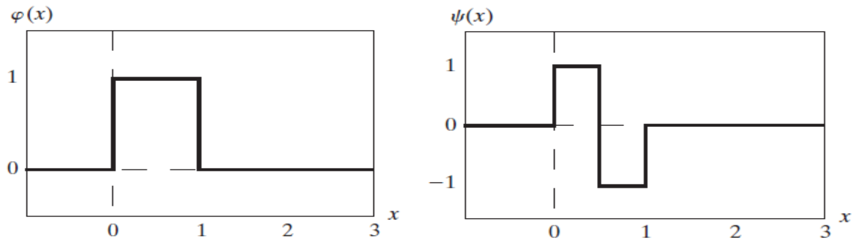
A hybrid of Gabor wavelet and neural networks is employed in [28] to extract facial features and construct models, while the nearest-neighbour classifier is used for classification. It is worth noting that the use of neural networks increases the system's complexity due to the requirements of more memory and time.

In [29], histogram equalization is used in combining with DWT and PCA for extracting features that may be affected by illumination variations. Compared with other approaches that use DWT only, this method consumes a lot of time in addition to its lower accuracy rate.

In this work, the proposed FR method attempts to overcome the drawback of the above approaches, which is represented by the algorithm's complexity. Therefore, the proposed work is based on the reduction in the size of memory usage, number of training iterations, and processing time to meet the real-time FR requirements. Furthermore, the achievement of high accuracy rate as well as low computational complexity has dramatically contributed to the success of the idea of implementing a real-time system for multi-access security.

3. Discrete wavelet transform

WT is the process of decomposing a signal into two components that are related to low and high frequencies. According to the type of signal that is being decomposed, WT comprises two types; continuous and discrete. As the name implies, the continuous WT deals with signals that are in continuous form, whereas the discrete signals are decomposed using DWT. The DWT convolves the input signal $f[n]$ with the impulse response of scaling and wavelet functions. The two functions of Haar wavelet are shown in Fig. 1 [30].



(a) Scaling function. **(b) Wavelet function.**

Fig. 1. Haar wavelet [30].

The scaling function $\varphi(x)$ is associated with the low pass filter (LPF) response $h[n]$ whereas the wavelet function $\psi(x)$ is associated with the high pass filter (HPF) response $g[n]$. DWT produces two coefficient signals $W_l[n]$ and $W_h[n]$, which correspond to the approximation and detailed signals, respectively. The convolution between $f[n]$ and $h[n]$ that produces $W_l[n]$ is illustrated as in Eqs. (1) and (2) [31].

$$W_l\,[n] = f[n] * h[n] \tag{1}$$

$$W_l[n] = \sum_{m=-\infty}^{\infty} f[n]h[2n-m] \tag{2}$$

Also, the detailed signal $W_h[n]$ is obtained according to Eqs. (3) and (4).

$$W_h\,[n] = f[n] * g[n] \tag{3}$$

$$W_h[n] = \sum_{m=-\infty}^{\infty} f[n]g[2n-m] \tag{4}$$

It is worth noting that the term $(2n)$ in Eqs. (2) and (4) refers to the down-sampling of the output signal by 2.

DWT decomposes the image two times; it starts with decomposing the rows and then the columns. As a result, four matrices of coefficients are constructed, which frequently named as high-high (HH), high-low (HL), low-high (LH) and low-low (LL) sub-bands. The variables L and H refer to the type of filters that produce the corresponding sub-band, as illustrated in Fig. 2 [32].

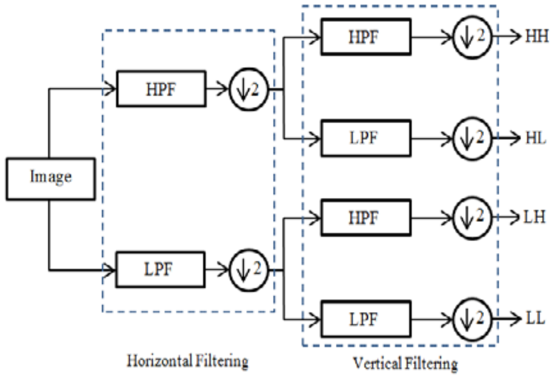


Fig. 2. First level of 2D-DWT [32].

The LL sub-band is called the approximation coefficients, and the remaining sub-bands represent the detailed coefficients. The 2nd level of DWT is obtained by further decomposing the LL matrix into four sub-band coefficients. Generally, the multi-level DWT is obtained by sequentially decomposing the successive approximation coefficients several times according to the desired number of levels.

4. The proposed FR method

The proposed FR method is illustrated in Fig. 3, where the initial step is selecting images from the database according to a specific process. The images in each database are sorted as training or testing images, where some images are chosen for training, and the others are collected in the testing set. For example, if each individual has 12 images in the database, *n* images ($n < 12$) can be selected for training, and the remaining (12-*n*) images are prepared for testing.

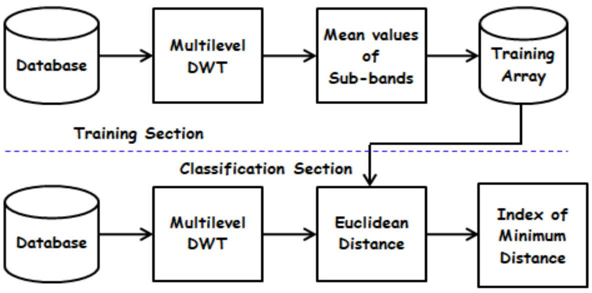


Fig. 3. Block diagram of the proposed FR method.

4.1. Training process

In the training process, three methods are used to extract facial features and construct the training array. The first step of the training process is common to all the methods, which is implemented by decomposing the images to a predefined level of DWT using db1 wavelet. The remaining procedure of each method is explained as follows:

- **Method1**: Five images of each subject in the database are selected to establish the training set, whereas the others are moved to the testing group. After applying the desired level of DWT to the training images, only the LL matrix of that level is taken into consideration, such that it is converted to a column vector, whereas all the remaining sub-bands are discarded. The obtained LL vectors for each individual are sequentially concatenated into a matrix. Hence, the mean of each row in this matrix is computed using Eq. (5):

$$\mu = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{5}$$

where μ, n, x and i are the mean, number of elements in each row, element's value and index of the element, respectively. Thus, the training features of each person's face are represented by one mean vector. Additionally, all the training vectors are concatenated into an array called training array, such that each column belongs to one person, where the columns are arranged according to the order of persons in the database. As a result, the size of training array is reduced by a factor of 5:1 from the LL sub-images' size.

- **Method2:** The same procedure of Method1 is followed in this method, but the mean vectors are normalized between 0 and 1 according to Eq. (6) [33].

$$N_j = \frac{\mu_j - min\ (\mu)}{max\ (\mu) - min\ (\mu)}\ , \qquad 1 \leq j \leq k \tag{6}$$

where N, j, min (μ), max (μ) and k are the normalized element, index of the element, minimum value of the mean vector, maximum value of the mean vector, and number of elements in the mean vector, respectively.

After that, each element in the normalized vectors is multiplied by a weight factor and converted to an integer number. This process helps in obtaining a wide disparity between the elements to make the recognition process more accurate. Furthermore, it reduces the utilized memory because the floating-point numbers require more memory than the integer numbers [34].

- **Method3**: This method takes into consideration all the sub-bands obtained from a specific level of DWT. The mean vector of each sub-band is formed in the same manner as in Method1. The maximum value in each of the HL, LH, and HH mean vector is appended to the LL mean vector to construct a new data vector. The reason for taking the entire LL mean vector into the construction of the new vector is the necessary information about the facial features that it includes.

4.2. Classification process

In the classification process, the testing image is decomposed to the same level of DWT that is used in the training process. Then, a column vector is constructed in the same manner used in each of the three methods to accommodate the form of the training array. Finally, the distance between the probe vector and each column in the training array, which represents the gallery vector, is computed as in the following equation:

$$d = \sqrt{\sum_{j=1}^{k}(y_j - \mu_j)^2} \quad (7)$$

where k, j, y and μ are number of elements in each vector, index of the element, element's value of the probe vector and element's value of the gallery vector, respectively. The decision is made according to the person's index that gives the minimum distance. For more precision, a threshold value must be defined to distinguish between persons that are members of such a database or not. If the distance is less than or equal to the threshold value, the person can be regarded as a known member; otherwise, he/she is a strange person.

5. Experiments

The experiments are carried out through the simulation of off-line FR system and the implementation of an access control system using real-time FR scheme.

5.1. Simulation results

The simulation task is accomplished using grey-scale images of two databases; Yale database [35] and a new one that is created for the proposed work, which is called multi-access security (MAS) database. For the Yale database, it includes 15 subjects, where each subject contributes with 11 images that each of which has a size of (320 × 243). Different facial expressions or configurations are included in each image such as centre-light, with glasses, happy, left-light, without glasses, normal, right-light, sad, sleepy, surprised, and wink. Some images contain a shadow and an unimportant region that is unrelated to a human face, such as the surrounding background. Therefore, the original image size is reduced to (192 × 192) by cropping the active region. For each individual in the database, five images are selected to form the training set, whereas the remaining six images are used to evaluate the classification rate. On the other hand, the MAS database includes 300 images for 30 individuals, i.e. ten images for each individual, where the image size is chosen to be (192 × 192). The training and testing sets are selected, such that they have an equal number of images, i.e. 150 images for each set.

Different levels of DWT are tested using db1 wavelet for image decomposition, and Euclidean distance for classification. The accuracy rates for the two databases using up to six levels of DWT are listed in Table 1.

Table 1. Accuracy rates of different DWT levels.

No. of Levels	Accuracy rate (%)					
	Yale database			MAS database		
	Method1	Method2	Method3	Method1	Method2	Method3
1	97.78	98.89	98.89	100	99.33	100
2	97.78	98.89	98.89	100	100	100
3	98.89	100	98.89	100	100	100
4	100	100	100	100	100	100
5	87.78	97.78	95.56	98.67	100	99.67
6	62.22	61.11	70	92.33	94.67	93.33

The desired accuracy rate is attained using four levels of DWT for the two databases and all methods. Furthermore, the same accuracy rate is achieved using different levels and methods with a disparity between the two databases. This disparity is due to the nature of each database, e.g. most images of the Yale database contain a shadow or a dark background on different sides. In contrast, this feature is unavailable in the MAS database. Regarding the three methods, it is evident from Table 1 that Method2 is the best for the two databases except for the Yale database when using the sixth level of DWT. However, for the MAS database, this method achieves less accuracy than the others in case of using the first level of DWT. In practice, the real-time FR applications require low processing data to speed up the system; especially in case of using a remote processing unit that wirelessly receives the data. The low accuracy rate that is obtained from applying the sixth level of DWT makes this level practically unacceptable. It is worth noting that each image of the MAS database is of size (192 × 192) and the size of LL matrix of the sixth level is (3 × 3). This small size of data includes inadequate information that prevents the system from attaining the desired accuracy rate. Therefore, the fifth level of DWT is suitable to implement a real-time access control system using the MAS database.

5.2. Comparative results

For precise evaluation of the best, a comparison with other work is necessary to be accomplished. Therefore, a comparison with some approaches that use WT and the Yale database is presented in Table 2.

Table 2. Comparison between different approaches.

Ref. No.	Wavelet type	No. of levels	No. of Training images	No. of Testing images	Training Time (s)	Testing Time (s)	Recognition Rate (%)
[15]	NA	5	6	5	NA	NA	90.3
[17]	db4	1	5	6	NA	NA	92
[18]	db3	3	3	4	NA	NA	100
[20]	DT-CWT	4	1	10	3	0.028	93.33
[24]	Various	5	5	6	0.017	0.014	98.89
[25]	db1	4	5	6	0.01	0.01	100
[26]	db1	1	5	6	NA	NA	98.89
[27]	NA	NA	NA	NA	NA	NA	98.75
[28]	Gabor	NA	4	7	NA	NA	94.48
[29]	Sym8	2	6	5	NA	NA	98.67
This work	db1	4	5	6	0.01	0.01	100

It is evident from Table 2 that the maximum accuracy rate has been achieved in [18, 25], and the proposed work. Although the processing time had been ignored in [18], one can deduce that the proposed method is more reliable, as explained below:

- In [18], a fusion of Radon and DWT was used to extract facial features, where this method consumes extra processing time and memory, compared to the use of DWT only.

- Four levels of DWT with the simplest type of wavelet (db1) are used in the proposed method, whereas three levels with db3 wavelet were used in [18]. It is worth noting that db3 is more complicated than db1, and the 4^{th} level of DWT reduces the LL matrix to the half size of that obtained from the 3^{rd} level. Therefore, the proposed method consumes less memory and time than that used in [18].
- In [18], seven images were used for training and testing, which means that four images were discarded from each person in the database. As a result, 60 images were excluded, and the number of used images was 105. Because of the nature of the reduced number of images used in [18], it is highly probable that these images contain high similarity that helps in attaining the 100 % recognition rate.

At first glance, it can be observed in Table 2 that the results of the proposed work and that obtained in [25] are identical. However, the two approaches have dissimilarities in their structures and operations, as explained below:

- Although the proposed method uses 4 GB of RAM, which is half the memory used in [25], it achieves the same processing speed. This means that the proposed method is cost-effective.
- In [25], the final LL matrix of each image, which is of size (12 × 12), is segmented to overlapped blocks, where each block is represented by two matrices; μ and Σ. Therefore, the size of the manipulated data became more extensive than that of the proposed work, which uses the mean of the whole sub-bands without any segmentation, as illustrated in Table 3.

Table 3. Comparative results of the manipulated data size.

Ref. No.	[25]	The proposed work		
		Method1	Method2	Method3
Size of LL	12 × 12	12 × 12	12 × 12	12 × 12
Size of block	6 × 6	-	-	-
Size of μ	36 × 1	144 × 1	-	147 × 1
Size of Σ	36 × 36	-	-	-
Total number of data elements	1332	144	144	147

As it is shown in Table 3, the proposed work uses less memory than that used in [25] due to the smaller size of the processed data, which is suitable for sending via wireless communication.

5.3. Implementation of an access control system

The implementation of the proposed FR method is carried out through the application of an access control system. This system manages the entry to public buildings that have multi-entrance gates via the recognition of incoming human faces using the proposed multi-level DWT method. The application comprises two entrance nodes and a central control unit. In each node, there is a camera that is connected to a Raspberry Pi (RasPi) board [36], which is used to take a video of the entry passage. The function of the RasPi is detecting faces from the video frames and then applying DWT to each face image. Figure 4 illustrates the proposed access control system.

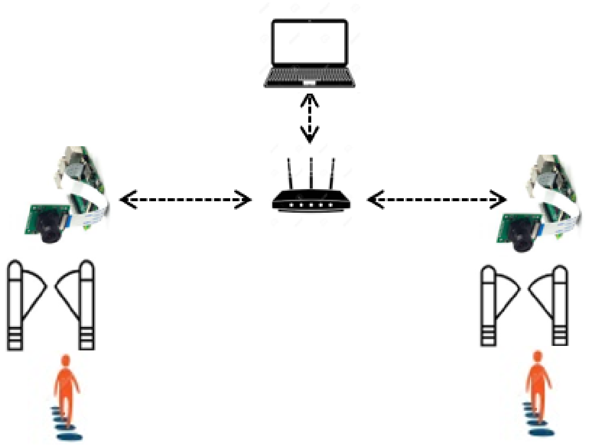


Fig. 4. The proposed access control system.

When a person enters the passage, the RasPi processes the video frames that are captured by the camera for face detection and extraction. Every four frames are simultaneously processed, and the Viola-Jones algorithm [37] is used to detect faces. It is worth noting that the entry looks like a turnstile, where only one person is allowed to enter the passenger in such a time.

The image of the detected face is extracted and decomposed using five levels of DWT, and hence, the procedure of Method2 is followed to construct the data vector that will be sent to the control unit. Due to the long distance between each node and the centre unit, which is approximately 25 meter, the direct connection cannot be established. Therefore, the connection is accomplished through a router using the TCP/IP communication method.

At the control unit, the received data vector from each node is saved into a dedicated file that can be used to retrieve the information of incoming persons. The squared Euclidean distances are calculated, as in Eq. (7), between the received vector and the trained array. Therefore, the index of the minimum distance refers to the anonymous person. For this implementation, the Euclidean distance must be determined by a threshold value, such that any distance value appears more than the threshold can be interpreted that the incoming person is considered as an unwanted member. In other words, any distance below the threshold value should be taken into consideration, which may belong to a person whose image is probably in the database. A high-level signal is sent back to the RasPi if the person is recognized as an identified member for further checking by the person in charge. If the incoming person does not match any individual in the database, the gate is opened for entry permission, and the corresponding information is stored for archiving. In case of a small size database, there is no need for the control unit, and the RasPi can do the recognition process. Because the RasPi has a small memory size, the information file must be periodically transferred to external memory to free up the RasPi memory.

The proposed access control system is tested using 100 persons; 20 persons are members of the MAS database, and the rest are unknown persons. The face detection part achieves about 82% of the accuracy rate, where the number of undetected faces is 18. This error may be occurred due to the use of Viola-Jones algorithm or the circumstances such as light density, non-frontal faces, blurring images and camera resolution. It is worth noting that the first stage of Viola-Jones algorithm depends on the detection of eyes, so it fails to detect non-frontal faces. This problem can be overcome using another algorithm that is capable of detecting non-frontal faces and also using a high-resolution camera.

In the recognition part, the system recognizes five unknown faces as members of the MAS database and two known faces as unknown persons. The threshold value is an essential factor that affects these results, where the calculation of the Euclidean distance requires the compatibility of the images' sizes. If the size of the detected face image is not equal to (192 × 192), the system resizes the image to this size to fit the original size of the training images. The resizing process may alter the structure of the facial features, which in turn affects the recognition result.

The process of transferring data between the control unit and the two nodes appears no errors, such that all the transmitted data are correctly received in time. The advantage of the TCP/IP over other protocols is the receiving guarantee, where the receiver sends an acknowledgement if the data is correctly received. Otherwise, the sender resends the data bits to ensure the arrival of data. The average time taken to accomplish the process of checking one face image is illustrated in Table 4.

Table 4. Processing time for one face image.

Detection time (ms)	Recognition time (ms)	Transferring time (ms)	Total average time (ms)
5	11	114	130

The fast speed of the proposed system can be observed in Table 4, where the processing time of one face image spends about 130 ms. Although the data transfer between each access node and the central unit takes about 114 ms, the system can track the events because the time between two accesses is more than 130 ms.

The Python programming language is used in the simulation and implementation of the proposed system. The RasPi 3 model *B* is used in each entrance gate, and the Linux OS is used on the control unit device that is implemented by a laptop with 2.4 GHz processor speed and 4 GB RAM.

6. Conclusion

A real-time system for a multi-access control is proposed in this study, which is based on the FR technique. The system is managed to prevent suspected or wanted people from entering specific locations such as residential buildings, campuses, supermarkets and malls. The proposed system utilizes a developed FR method that has a simple and accurate procedure. Three methods are examined to extract facial features with a minimum data size, where they use a multi-level DWT and statistical calculations (mean of the selected frequency bands). The method that uses the normalized values of the mean vectors achieves the best recognition rate. It satisfies the requirements of low processing time and minimum utilized memory, as well as the high recognition rate. For classification, the Euclidean distance is used to designate the closest person to the testing image. In the simulation section, the results show the superiority of the proposed FR scheme over others that use Yale database and WT. In the implementation part, five levels of DWT are used in a real-time multi-access control system. The system comprises two access nodes that wirelessly communicate with the control unit using the TCP/IP communication method. The advantage of TCP/IP method is the guarantee of receiving the data by the control unit. The accuracy of face detection is approximately 82% using the Viola-Jones algorithm, whereas the real-time FR achieves about 91.46%.

The suggestions for future research can be viewed on the site of face detection improvements and testing the system using an extensive database.

Nomenclatures

f	Input signal
g	High pass filter response
h	Low pass filter response
W_h	Detailed coefficient signal
W_l	Approximation coefficient signal

Greek Symbols

μ	Mean
Σ	Covariance
φ	Scaling Function
ψ	Wavelet Function

Abbreviations

2D	Two-Dimension
db1	Daubechiese Wavelet type 1
db3	Daubechiese Wavelet type 3
db4	Daubechiese Wavelet type 4
DCT	Discrete Cosine Transform
DFT	Discrete Fourier Transform
DT-CWT	Dual-Tree Complex Wavelet Transform
DWT	Discrete Wavelet Transform
FR	Face Recognition
GB	Giga Byte
GHz	Giga Hertz
HH	High-High
HL	High-Low
HMM	Hidden Markov Model
HPF	High Pass Filter
KNN	K-Nearest Neighbour
LBP	Local Binary Pattern
LDA	Linear Discriminate Analysis
LH	Low-High
LL	Low-Low
LPF	Low Pass Filter

MAS	Multi-Access Security
NA	Not Available
OS	Operating System
PCA	Principal Component Analysis
RAM	Random Access Memory
RasPi	Raspberry Pi
SVM	Support Vector Machine
TCP/IP	Transmission Control Protocol/Internet Protocol
WT	Wavelet Transform

References

1. El-Hallaq, M. (2019). A proposed template image matching algorithm for face recognition. *2019 Institute of Electrical and Electronics Engineering (IEEE) 7th Palestinian International Conference on Electrical and Computer Engineering (PICECE)*, Gaza, Palestine, 1-6.
2. Choi, S.; and Jeong, G. (2010). Shadow compensation using fourier analysis with application to face recognition. *Institute of Electrical and Electronics Engineering (IEEE) Signal Processing Letter*, 18(1) 23-26.
3. Farhan, H.; Al-Muifraje, M.; and Saeed, T. (2020). A new model for pattern recognition. *Computers and Electrical Engineering*, 83(2020), 106602.
4. Kafai, M.; Eshghi, K.; and Bhanu, B. (2014). Discrete cosine transform locality-sensitive hashes for face retrieval. *Institute of Electrical and Electronics Engineering (IEEE) Transactions on Multimedia*, 16(4), 1090-1103.
5. Yanyun, Q.; Nanning, Z.; Cuihua, L.; and Zejian, Y. (2004). Sequential updating algorithm for extracting the basis of Karhunen-Loeve transformation. *2004 International Conference on Image Processing,* Singapore, 3, 1529-1532.
6. Anggo, M.; and Arapu, L. (2018). Face recognition using fisherface method. *Journal of Physics Conference Series*, 1028(1), 1-9.
7. Farhan, H.; Al-Muifraje, M.; and Saeed, T. (2016). Using only two states of discrete HMM for high-speed face recognition. *Al-Sadiq International Conference on Multidisciplinary in IT and Communication Techniques Science and Applications,* Baghdad, Iraq, 218-222.
8. Ahonen, T.; Hadid, A.; and Pietikainen, M. (2006). Face description with local binary patterns: Application to face recognition. *Institute of Electrical and Electronics Engineering (IEEE) Transactions on Pattern Analysis and Machine Intelligence*, 28(12), 2037-2041.
9. Gumus, E.; Kilic, N.; Sertbas, A.; and Ucan, O. (2010). Evaluation of face recognition techniques using PCA, wavelets and SVM. *Expert System with Applications*, 37(9), 6404-6408.
10. Abbas, H.; Altameemi, A.; and Farhan, H. (2019). Biological landmark vs quasi-landmarks for 3D face recognition and gender classification. *International Journal of Electrical and Computer Engineering*, 9(5), 4069-4076.
11. Zhang, T.; Zheng, W.; Cui, Z.; Zong, Y.; Yan, J.; and Yan, K. (2016). A deep neural network-driven feature learning method for multi-view facial expression recognition. *Institute of Electrical and Electronics Engineering (IEEE) Transactions on Multimedia,* 18(12), 2528-2536.

12. Abiantun, R.; Prabhu, U.; and Savvides, M. (2014). Sparse feature extraction for pose-tolerant face recognition. *Institute of Electrical and Electronics Engineering (IEEE) Transactions on Pattern Analysis and Machine Intelligence*, 36(10), 2061-2073.
13. Farhan, H.; Al-Muifraje, M.; and Saeed, T. (2017). A novel face recognition method based on one state of discrete Hidden Markov Model. *2017 Annual Conference on New Trends in Information and Communications Technology Applications (NTICT)*, Baghdad, Iraq, 252-257.
14. Meade, M.; Sivakumar, S.; and Phillips, W. (2005). Comparative performance of principal component analysis, Gabor wavelets and discrete wavelet transforms for face recognition. *Canadian Journal of Electrical and Computer Engineering*, 30(2), 93-102.
15. Sujaritha, M.; and Annadurai, S. (2007). Face recognition using wavelet transform and locally discriminating projection. *International Conference on Computational Intelligence and Multimedia Applications (ICCIMA 2007)*, Sivakasi, Tamil Nadu, 436-440.
16. Liu, C.; and Dai, D. (2009). Face recognition using dual-tree complex wavelet features. *Institute of Electrical and Electronics Engineering (IEEE) Transactions on Image Processing*, 18(11), 2593-2599.
17. Lihong, Z.; Ying, S.; Yushi, Z.; Cheng, Z.; and Xili, Z. (2009). Face recognition based on image transformation. *2009 WRI Global Congress on Intelligent Systems*, Xiamen, 418-421.
18. Jadhav, D.; and Holambe, R. (2009). Feature extraction using Radon and wavelet transforms with application to face recognition. *Neurocomputing*, 72(7-9), 1951-1959.
19. Sellahewa, H.; and Jassim, S. (2010). Image-Quality-Based adaptive face recognition. *Institute of Electrical and Electronics Engineering (IEEE) Transactions on Instrumentation and Measurement*, 59(4), 805-813.
20. Priya, K.; and Rajesh, R. (2010). Local fusion of complex dual-tree wavelet coefficients based face recognition for single sample problem," *Procedia Computer Science*, 2, 94-100.
21. Sharma, P.; Arya, K.; and Yadav, R. (2013). Efficient face recognition using wavelet-based generalized neural network. *Signal Processing*, 93(6), 1557-1565.
22. Huang, Z.; Li, W.; Wang, J.; and Zhang, T. (2015). Face recognition based on pixel-level and feature-level fusion of the top-level's wavelet sub-bands. *Information Fusion*, 22, 95-104.
23. Muqeet, M.; and Holambe, R. (2016). Local appearance-based face recognition using adaptive directional wavelet transform. *Journal of King Saud University - Computer and Information Science*, 31(2), 161-174.
24. Farhan, H.; Abbas, H.; and Shahadi, H. (2019). Combining multi-resolution wavelets with principal component analysis for face recognition. *Proceedings of International Conference on Information and Communication Technology (ICICT '19)*, Baghdad, Iraq,154-159.
25. Farhan, H.; Al-Muifraje, M.; and Saeed, T. (2019). Face recognition system based on continuous one-state model. *AIP Conference Proceedings*, 2144(050001), 1-9.

26. Vishwakarma, V.; Dalal, S.; and Sisaudia, V. (2018). Efficient feature extraction using dwt-dct for robust face recognition under varying illuminations. *2018 2nd Institute of Electrical and Electronics Engineering (IEEE) International Conference on Power Electronics, Intelligent Control and Energy Systems (ICPEICES)*, Delhi, India, 982-987.
27. Aldhahab, A.; Alobaidi, T.; Althahab, A.; and Mikhael, W. (2019). Applying multiresolution analysis to vector quantization features for face recognition. *2019 Institute of Electrical and Electronics Engineering (IEEE) 62nd International Midwest Symposium on Circuits and Systems (MWSCAS)*, Dallas, TX, USA, 598-601.
28. Dumitrescu, C.; and Dumitrache, I. (2019). Combining neural networks and global gabor features in a hybrid face recognition system. *2019 22nd International Conference on Control Systems and Computer Science (CSCS)*, Bucharest, Romania, 216-222.
29. Yadav, J.; Rajpal, N.; and Mehta, R. (2019). An improved illumination normalization and robust feature extraction technique for face recognition under varying illuminations. *Arabian Journal for Science and Engineering*, 44, 9067-9086.
30. Gonzalez, R.; and Woods, R. (2017). *Digital image processing.* 4th edition, Pearson.
31. Ambika, D.; and Radha, V. (2012). A comparative study between discrete wavelet transform and linear predictive coding. *2012 World Congress on Information and Communication Technologies*, Trivandrum, 965-969.
32. Zhang, B.; Zhang, H.; and Ge, S. (2004). Face recognition by applying wavelet subband representation and kernel associative memory. *Institute of Electrical and Electronics Engineering (IEEE) Transactions on Neural Networks*, 15(1), 166-177.
33. Li, S.; and Jain, A. (2015). *Encyclopedia of biometrics*. 2nd edition, Springer Science and Business Media, New York.
34. Microprocessor Standards Committee. (2019). IEEE standard for floating-point arithmetic. *Institute of Electrical and Electronics Engineering (IEEE) Standard 754-2019 (Revision of IEEE 754-2008)*, 1-84.
35. Belhumeur, P.; Hespanha, J.; and Kriegman, D. (1997). Eigenfaces vs. Fisherfaces: recognition using class specific linear projection. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 19(7), 711-720.
36. Marot, J.; and Bourennane, S. (2017). Raspberry Pi for image processing education. *2017 25th European Signal Processing Conference (EUSIPCO)*, 2364-2366.
37. Viola, P.; and Jones, M. (2004). Robust real-time face detection. *International Journal of Computer Vision*, 57(2), 137-154.