American Journal of Applied Sciences

Original Research Paper

Schoenberg Logarithmic Image Similarity in Prewitt-Gabor-Zernike Domain

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Article history
Received: 22-04-2017
Revised: 01-07-2017
Accepted: 26-09-2017

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Abstract: This paper represents a new approach for face recognition that incorporates Prewitt edge detection, Gabor filter and Zernike moments to transform the image into a unified domain. On this joint domain, five distance metrics are constructed using Schoenberg transform for the purpose of defining efficient similarity measures for holistic face recognition. The proposed Schoenberg similarity applies Schoenberg transform to the logarithm of five existing distance metrics: Minkowski, City-Block, Euclidean, Soergel and Lorentzian metrics. The constructed Schoenberg logarithmic metrics are called SL-Minkowski, SL-City-Block, SL-Euclidean, SL-Soergel and SL-Lorentzian. These distance metrics are utilized as similarity measures after being normalized over the range [0,1] for fair comparison with existing measures. The proposed Schoenberg system can resist three problems: Change in illumination, pose and facial expression. Simulation results show that the proposed distance measures have superior performance as compared to the classical metrics: Structural Similarity Index Measure (SSIM) and Feature-based Similarity Measure (FSIM). Performance criteria are the recognition rate and the recognition confidence, defined as the similarity difference between the best match and the second-best match in the face database.

Keywords: Face Recognition, Edge Detection, Gabor Filter, Zernike Moments, Schoenberg Transform, Image Similarity

Introduction

Face recognition has become one of the most significant of image analysis and computer vision. It is a multidisciplinary filed with many unresolved problems that involve several other fields especially mathematics, numerical analysis, statistics, computer science and electronic engineering (Parmar and Mehta, 2013; Vu *et al*., 2016; Nagi *et al*., 2008; Alwakeel and Shaaban, 2010). One of the main streams in face recognition is to recognize a given face image in the sense of similarity with some image in a large face-database. This process involves a lot of unresolved difficulties (Jafri and Arabnia, 2009; Sang *et al*., 2016; Kakade, 2016).

Images of the same person could be very different if subjected to changes in lighting, pose and facial expression. If these change are larger than some limits, systems would not be able to recognize the input image (Mahto and Yadav, 2014; Murphy-Chutorian and Trivedi, 2009; Nolazco-Flores *et al*., 2015).

Edge detection is a very important area in the field of computer vision. Edges define the boundaries between important regions in an image, which helps in segmentation and object recognition (Singh, 2013). Edge detection is much more stable to changes in illumination (Neto, 2014). This process would be included in our approach as explained later.

Gabor filter has been proposed in 1946 by Gabor (1946) and extended into two-dimensional function by Daugman (1985). Gabor filter is resistant against a moderate change of illumination (Kamarainen *et al*., 2006), but not in presence of a big change in illumination. To handle such a problem, we invoke Prewitt edge detection to improve the performance of Gabor filter.

A powerful approach for face recognition and image analysis is through the use of image moments (Cho-Huak and Chin, 1988; Imran *et al*., 2016; Rahman *et al*., 2016; Singh and Sahan, 2013; Hajati *et al*., 2012). Zernike moments approach (Zernike, 1934) is one of the well-known image analysis and face recognition techniques, introduced in 1934. Zernike moments approach provides many advantages such as feature representation and feature space reduction, while it provides more details about the facial image (Hashim and Hussain, 2014).

Features extracted by Gabor filters have large dimensionality. However, applying Zernike moments can reduce dimension. Despite the powerful features provided by Zernike moments, they may not be decisive in recognizing a face image in a large face-database. However, this failure may be due to the inefficient exploitation of hidden capabilities of Zernike moments, which we try to explore.

In this study we present a hybrid method to incorporate special distance features with edge-detection and Gabor filtering to enhance the discriminative power of Zernike moments in the process of face recognition. The image is first transform into Prewitt-Gabor-Zernike domain to extract features on which five deferent distance metrics based on Schoenberg transform (Bin *et al.*, 2002) are used to define new Schoenberg similarities in the joint Prewitt-Gabor-Zernike domain. Schoenberg transform is used to extend the distance defined by five classical metrics: Minkowski, City-Block, Euclidean, Soergel and Lorentzian. The proposed approach outperforms existing similarity measures if used for face recognition.

The paper is organized as follows: Section 2 presents a theoretical background on Gabor filter, Zernike moments, edge detection, metric distances, image structural similarity and the feature similarity. Section 3 describes the proposed measures, while experimental results are presented along with comparisons in Section 4.

Background

In this section some related theoretical principles are explained. A brief details of the Gabor filter and the Zernike moments approach are presented, then notions of the space and the distance metric are summarized. Also, the convention approaches, the Structural Similarity Index (SSIM) and the Feature Similarity Index (FSIM) are used to handle the structural distance between 2D objects.

Gabor Filter

The two-dimensional Gabor filter function is defined mathematically as follows (Grigorescu *et al.*, 2002):

$$H_{\lambda,\psi,\gamma,\theta}(x,y)=e^{-\left(\frac{x'^2+\gamma^2 y'^2}{2\sigma^2}\right)}\cos\left(\frac{2\pi x'}{\lambda}+\psi\right) \quad (1)$$

where, $x' = x\cos(\theta) + y\sin(\theta)$, $y' = -x\sin(\theta) + y\cos(\theta)$, λ represents the wavelength of the sinusoidal factor, θ represents the orientation of the normal to the parallel stripes of a Gabor function, ψ is the phase offset, σ is the standard deviation of the Gaussian envelope and $\gamma = \sigma y/\sigma x$ is the spatial aspect ratio, which specifies the elliptic city of the support of the Gabor function. The range of x and y is as follows:

$$x_{\max} = \max(1, x_m);\ where$$
$$x_m = \max(|N\sigma_x\cos(\theta)|, |N\sigma_y\sin(\theta)|);\ x_{\min} = -x_{\max}$$

$$y_{\max} = \max(1, y_m);\ where$$
$$y_m = \max(|N\sigma_x\sin(\theta)|, |N\sigma_y\cos(\theta)|);\ y_{\min} = -y_{\max}$$

where, N is the filter size we set:

$$\psi = 0, \gamma = 0.7, \sigma = 1.5, \theta \in \left\{\frac{n_1\pi}{8} \mid 0 \le n_1 \le 8, n_1 \in \mathbb{Z}\right\},$$
$$\lambda \in \{10n_2 + 2 \mid 0 \le n_2 \le 25, n_2 \in \mathbb{Z}\}$$

Zernike Moments

In polar coordinate (r,θ), the Zernike radial polynomials $R_{pq}(r)$ are defined as (Bin and Jia-xiong, 2002; Hashim and Hussain, 2014):

$$R_{pq}(r)=\sum_{k=0}^{\frac{p-|q|}{2}}\frac{(-1)^k(p-k)!}{k!\left(\frac{p+|q|}{2}-k\right)!\left(\frac{p-|q|}{2}-k\right)!}r^{p-2k} \quad (2)$$

where, $p \in Z$, $p \neq 0$ and q is a non-zero integer subject to the following constrains: $|p-q|$ is even and $|q| \le p$. The two-dimensional Zernike moments is defined by the following form:

$$Z_{pq}=\frac{p+1}{\pi}\int_0^{2\pi}\int_0^1 R^*_{pq}(r)e^{-jq\theta}f(r,\theta)rdrd\theta,\quad |r|\le 1 \quad (3)$$

To approximate and compute them in the discrete form we perform a linear transformation of the image Cartesian coordinates (i,j) from the inside of the square $\{(i,j): i,j = 0,1,..., N-1\}$ to the inside of the unit circle $\{(r,\theta): |r| \le 1\}$ to get the following discrete form:

$$Z_{pq}=\frac{p+1}{N-1}\sum_{j=0}^{N-1}\sum_{i=0}^{N-1}R_{pq}(r_{ij})e^{-jq\theta}f(i,j) \quad (4)$$

where:

$$r_{ij}=\sqrt[2]{x_i^2+y_i^2};\ x_i=\frac{2i}{N-1}-1,$$
$$y_i=\frac{2j}{N-1}-1, \theta_{ij}=\tan^{-1}\left(\frac{y_j}{x_i}\right) \quad (5)$$

Features of an image f can be represented by a vector of selected Zernike moments, V_f, to be used in the design process of image similarity measures (here the purpose is face recognition; but they have other applications, like in emotion recognition (Lajevardi and Hussain, 2010a).

Edge Detection

Edge information plays a vital role in applications of image processing. The edge information is effectively used in iris recognition, face recognition, fingerprint, texture analysis and palmistry analysis. Here, we have used edge detection as a feature extraction method to extract edges from facial images (Karande and Talbar, 2009).

Prewitt Filter

Prewitt edge detection technique is selected due to efficiency and simplicity in the single mask. Fig. 1 shows typical Prewitt edge detection masks. In this technique, the edges are detected by convolving horizontal and vertical masks G_x and G_y respectively, through the image. The masks are orthogonal to each other and use to measure the difference among the adjacent pixels grey level in vertical and horizontal direction. The approximate gradient is $|G| = |G_x| + |G_y|$. The detected edges are displayed by combining the horizontal and vertical edges (Seif *et al*., 2010):

Metric Distance

In this subsection we consider five metrics (distance measurements) for the vectors in R^n space. These metrics will be used later to design similarity measurements.

Metric Space

Let X be a set. A function d: $X\times X \to R$ is said to be metricon X if, for all x, y, $z \in X$, it satisfy the following conditions:

- $d(x, y) \geq 0$ (*non-negativity*)
- $d(x, y) = 0$ if and only if $x = y$ (separation or self-identity axiom);
- $d(x, y) = d(x, y) =$ (*symmetry*)
- $d(x, y) \leq d(x, z) + d(z, y)$ (triangle inequality)

A metric space (X, d) is a set X together with a metric d on X (Bin *et al*., 2002).

Important metric distances considered in this study are**:** Minkowski, City-Block, Euclidean, Soergel and Lorentzian. Let X, $Y \in R^n$ be n-dimensional vectors, where $X = \{x_1, x_2, x_3,..., x_n\}$ and $Y = \{y_1, y_2,..., y_n\}$. The above metrics are defined as follows (Cha, 2007; Chen and Chu, 2005).

Classical Distance Measures

The Euclidean distance between vectors X, Y is computed by:

$$d_{Euc}(X,Y) = \sqrt[2]{\sum_{i=1}^{n} |x_i - y_i|^2} \tag{6}$$

The City block distance between two vectors X, Y vectors is computed by:

$$d_{CB}(X,Y) = \sum_{i=1}^{n} |x_i - y_i| \tag{7}$$

The Soergel distance between two vectors X, Y vectors is defined by the following form:

$$d_{Sg}(X,Y) = \frac{\sum_{i=1}^{n} |x_i - y_i|}{\sum_{i=1}^{n} \max(x_i, y_i)} \tag{8}$$

The Lorentzian distance between two X, Y vectors is defined by the following form:

$$d_{Lor}(X,Y) = \sum_{i=1}^{n} \ln(1 + |x_i - y_i|) \tag{9}$$

The Minkowski distance between two vectors X and Y is defined by the following form:

$$d_{MK}(X,Y) = \sqrt[t]{\sum_{i=1}^{n} |x_i - y_i|^t};\ t \geq 1 \tag{10}$$

The above measurements can be used to investigate the similarity between images using the mean-squared error (Wang and Bovik, 2009). However, the mean-squared error considered a weak tool for the image similarity. The more powerful tool for the image similarity is explained below.

Image Structural Similarity Measure (SSIM)

Wang *et al*. (2004) introduced a new image quality index, named the Structural Similarity Index Measure (SSIM) based on the statistical structure of pixel intensities. The SSIM compares between two images: x and y that defined as follows:

$$SSIM = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \tag{11}$$

where, μ_x and μ_y represent the local means of images X and Y, respectively, σ_x and σ_y represent the standard deviations, σ_{xy} is the covariance of the two images, σ_x^2 and σ_y^2 represent the variances, respectively, while the constants C_1 and C_2 are defined as $C_1 = (K_1L)^2$ and $C_2 = (K_2L)^2$ with $K_1 = 0.01$, $K_2 = 0.03$ and $L = 255$ (Dosselmann and Yang, 2011).

$$G_x = \begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix}; \quad G_y = \begin{bmatrix} -1 & -1 & -1 \\ 0 & 0 & 0 \\ 1 & 1 & 1 \end{bmatrix}; \quad |G| = |G_x| + |G_y|$$

Fig. 1. The horizontal and vertical Prewitt edge detection masks.

Feature Similarity Index for Image Quality Assignment (FSIM)

Zhang *et al*. (2011) proposed a novel image quality index called feature similarity index measure based on the Phase Congruency (PC) and the Gradient Magnitude (GM). The FSIM between $f_1(x)$ and $f_2(x)$ is defined as follows:

$$FSIM = \frac{\sum_{x\in\Omega} S_L(x).PC_m(x)}{\sum_{x\in\Omega} PC_m(x)} \tag{12}$$

where, x represents position in the image, $PC_m(x) = \max(PC_1(x), PC_2(x))$ is the maximal Phase Congruency (PC) value at the position x between the two images, $S_L(x) = S_{PC}(x)$. $S_G(x)$, $S_{PC}(x)$ is the similarity measure for $PC_1(x)$ and $PC_2(x)$, $S_G(x)$ is the similarity measure for two gradient magnitude values at the position x between the two images and Ω represent the whole image spatial domain.

Schoenberg Logarithmic Distance Metrics

In this section we will construct metric distances based on the Schoenberg transform metric.

Schoenberg Transform Metric (Bin *et al*., 2002):

Given a metric space (X, d) and $a > 0$ then, the Schoenberg transform metric is a functional transform metric on X, defined by $(1-e^{-ad(x,y)})$.

Theorem

If (X, d) is a metric space, then $(X, \hat{d})$ is also metric space, where, $\hat{d}(x,y) = In(1 + d(x,y))$ (Ali *et al*., 2017).

Schoenberg Logarithm Metrics

Using the Theorem and definition above, five metric distances are designed as follows.

Schoenberg Logarithm Euclidean Distance

The SL-Euclidean distance between vectors X, Y is defined by:

$$d_{SL-Euc}(X,Y) = \ln\left(2 - e^{-\alpha\sqrt{\sum_{i=1}^{n}|x_i - y_i|^2}}\right) \tag{13}$$

Schoenberg Logarithm Cityblock Distance

SL-Cityblock distance between two vectors X, Y is defined by:

$$d_{SL-CB}(X,Y) = \ln\left(2 - e^{-a}\sum_{i=1}^{n}|x_i - y_i|\right) \tag{14}$$

Schoenberg Logarithm Soergel Distance

The SL-Soergel distance between two vectors X, Y vectors is defined by the following form:

$$d_{SL-Sg}(X,Y) = \ln\left(2 - e^{-\alpha\left(\frac{\sum_{i=1}^{n}|x_i - y_i|}{\sum_{i=1}^{n}\max(x_i, y_i)}\right)}\right) \tag{15}$$

Schoenberg Logarithm Lorentzian Distance

The SL-Lorentzian distance between two vectors X and Y is defined by the following form:

$$d_{SL-Lor}(X,Y) = \ln\left(2 - e^{-\alpha\sum_{i=1}^{n}\ln(1+|x_i - y_i|)}\right) \tag{16}$$

Schoenberg Logarithm Minkowski Distance

The SL-Minkowski distance between two X, Y vectors is defined by the following form:

$$d_{SL-MK}(X,Y) = \ln\left(2 - e^{-\alpha\left(\sum_{i=1}^{n}|x_i - y_i|^t\right)^{\frac{1}{t}}}\right); \quad t \geq 1 \tag{17}$$

Normalized Distance Similarity in the Zernike Domain

Let x and y are two images and assume we have two vectors V_x and $V_{y'}$ that contain a specific n-dimensional selected feature of Zernike moments of the x and y. Also, assume d is the given distance metric between V_x and $V_{y'}$. The double-normalization is used to normalize the similarity as follows:

$$s = \frac{d_o}{\max(d_o)}; \quad \text{with } d_o = \left(1 - \frac{d}{\max(d)}\right) \tag{18}$$

Which has the property that $0 \leq s \leq 1$.

The normalization step is considered here to get a fair comparison with existing similarity measures.

Implementation and Results

Test Environment

The FEI face database has been chosen: It contains a set of face images taken between June 2005 and March 2006 at the Artificial Intelligence Laboratory of FEI in São Bernardo do Campo, São Paulo, Brazil. There are 14 images for each of its 200 individuals, summing up to 2800 images. All images are colored and taken against a white homogenous background in an upright frontal position with profile rotation of up to about 180 degrees. Scale might vary about 10% and the original size of each image is 640×480 pixels. All images in FEI are faces of students and staff at FEI, between 19 and 40 years old with distinct appearance, hairstyle and adorns. The numbers of male and female subjects are exactly the same and equal to 100 (FEI Face Database). Figure 2 shows an example of face images representing different poses for one person from the FEI face database.

The (ORL Face Database) contains samples from 40 individuals, each providing 10 different images. For some subjects, the images were taken at different times. The facial expressions (open or closed eyes, smiling or non-smiling) and occlusion (glasses or no glasses) also vary. The images were taken with a tolerance for tilting and rotation up to 20 degrees. There is also some variation in the scale of up to 10%. All images are gray scale and normalized to a resolution of 112×92 pixels.

System Implementation

The FEI and ORL database contain 200 and 40 face images, respectively, three of them is selected as a reference image. For the reference person, four images with four different poses have been used: Three as a test image and one as a part of the training database (Fig. 3). The proposed recognition system consists of the following steps:

- Reading the Images: The system can read any type of extension (JEPG, TIF,…,etc)
- Image Pre-Processing: The following pre-processing processes are needed before applying the proposed system
- Modifying image scales: All images must be square and have even dimensions
- Gray-scale: Converting the images into gray level.
- Features extraction: This step involves incorporating Prewitt edge detection, Gabor filter and ZMs. The use of Prewitt and Gabor filter together gives the power to recognize the persons in presence of a big change in illumination (Fig. 4)

The features which are extracted by Gabor filters have large dimensionality. However, the large dimension of Gabor features is reduced by taking Zernike transform. This step reduces the time of recognition in different poses (Fig. 5).

Figure 4a shows that Gabor filter mistakes the person under a big change in illumination, but when improved as Prewitt-Gabor combination the target person is recognized as in Fig. 4b.

Sub-Fig. 5a and b show that Gabor's and Zernike's approaches can't recognize the person when used separately, but a combination of them has the power of correct recognition under different poses as shown in Fig. 5c.

This step is illustrated by the following points:

- For an image x, its edge-image is found as follows: $x_e = x*h$, where $h = |G|$ Prewitt mask as in Fig. 1, the operation '*' is the 2D convolution.
- $S = H^* x_e$; where H is the Gabor filter mask as in Equation (1).
- V_s = Zernike (S); given by the following moments of S:

$$V_s = \begin{bmatrix} |Z_{2,0}|,|Z_{2,2}|,|Z_{3,1}|,|Z_{3,3}|,|Z_{4,0}|,|Z_{4,2}|,|Z_{4,4}|,|Z_{5,1}|,|Z_{5,3}|, \\ |Z_{5,5}|,|Z_{6,0}|,|Z_{6,2}|,|Z_{6,4}|,|Z_{6,6}|,|Z_{7,1}|,|Z_{7,3}|,|Z_{7,5}|,|Z_{7,7}|,|Z_{8,0}|, \\ |Z_{8,2}|,|Z_{8,4}|,|Z_{8,6}|,|Z_{8,8}|,|Z_{9,1}|,|Z_{9,3}|,|Z_{9,5}|,|Z_{9,7}|,|Z_{9,9}|] \end{bmatrix}$$

- Proposed measures: These feature vectors (V_s) are subjected to the proposed similarity measures: SL-City block, SL-Euclidean, SL-Soergel, SL-Lorentzian and SL-Minkowski.
- Normalization/Recognition: The proposed similarity measures and existing measures are normalized using Equation (18) for fair comparison.

The recognition phase starts after normalization. The best match is the face that gives maximal similarity with the test image. The implementation is detailed as per the diagram in Fig. 6.

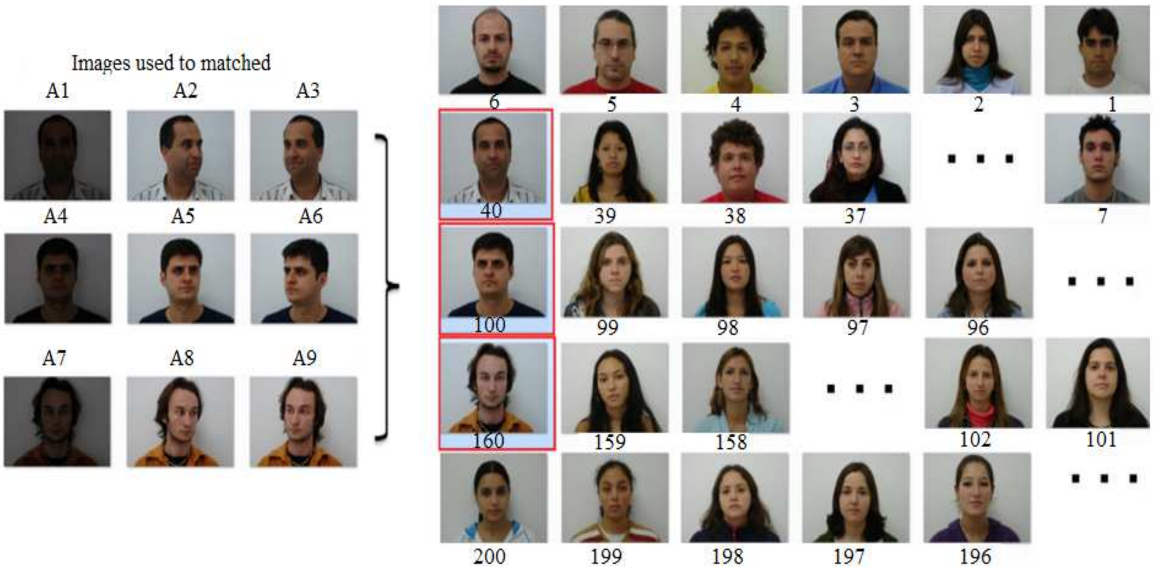
Simulation Results

The proposed and existing systems have been implemented using MATLAB. Comparative analysis has been done to test the performance of the proposed similarity metrics versus the classical metrics as shown in Fig. 7-11. Comparisons has been made with SSIM, FSIM and the Zernike moments method (Singh *et al.*, 2011). The scores of similarity provided by the proposed metrics are more robust and give more confidence. Recognition confidence is introduced here as a performance measure (in addition to the correct recognition rate). It is defined as the similarity difference between the best match and the second-best match in the database.

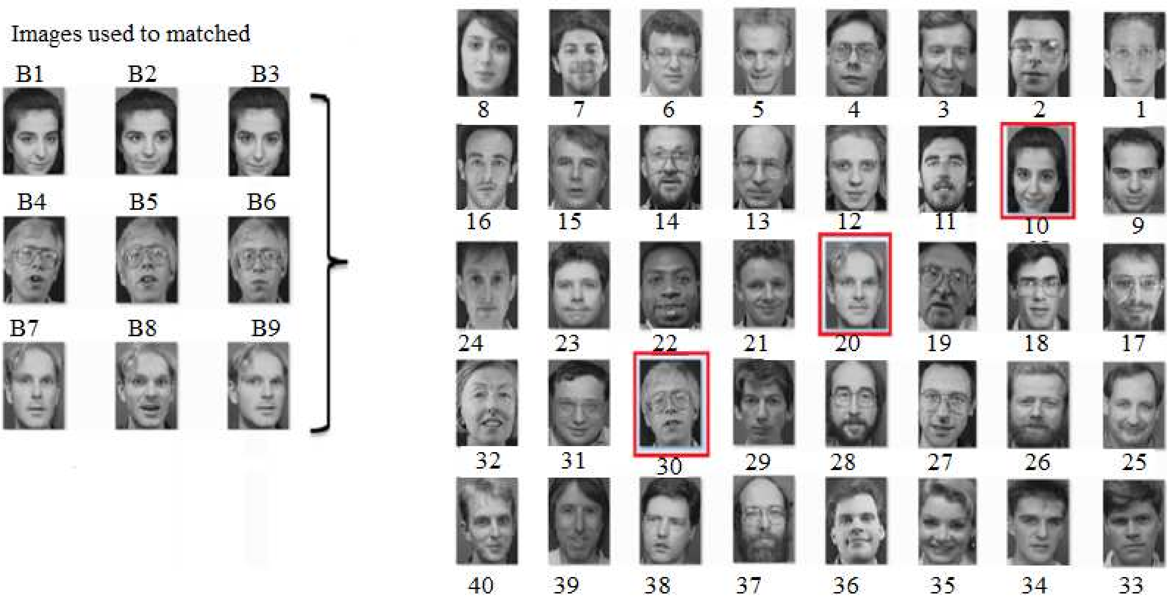
Moreover, the SL-Minkowski metric approach provides better results as compared to other methods through minimizing the confusion as shown in Fig. 12 and 13.

Table 1 shows recognition rate for the proposed metrics and existing methods. Table 2 and 3 show the confidence rate (difference between most likely face (best match) and the second-most likely face). The mark (----) in tables indicates a mistake in recognition.

Fig. 2. An example of face with different poses from the FEI face database.

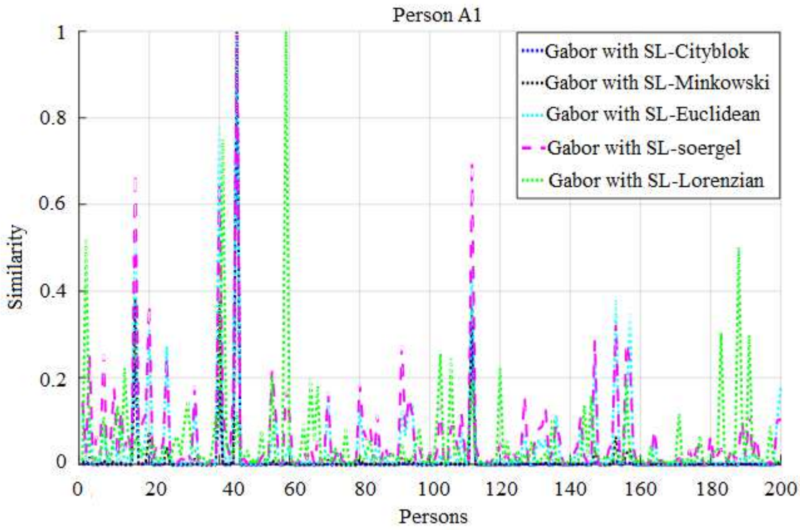


(a)

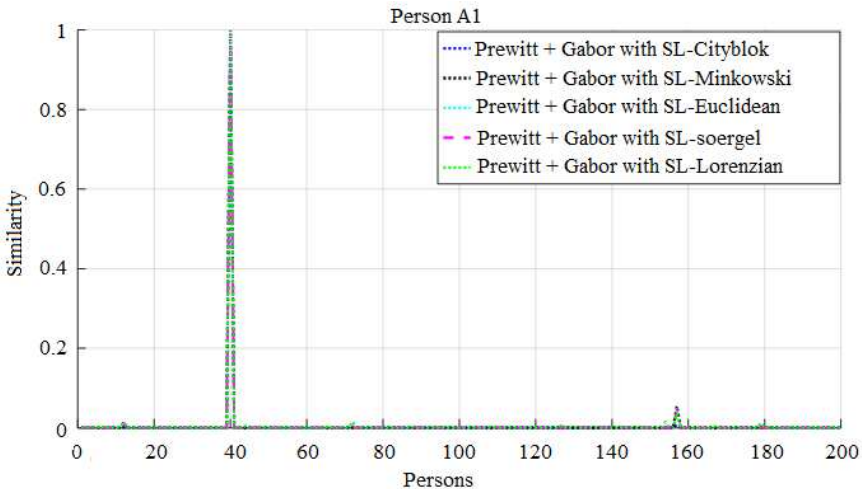


(b)

Fig. 3. An example of the test face database (a) from FEI database (b) from ORL database.

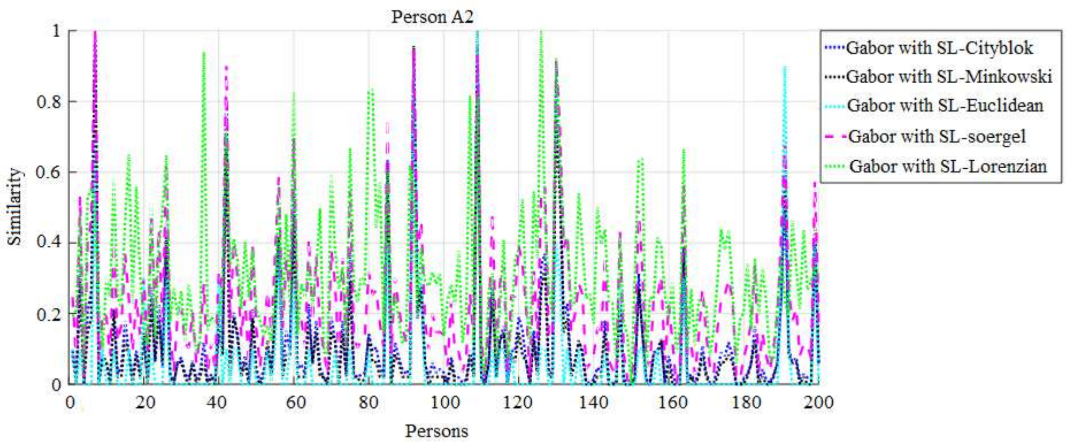


(a)



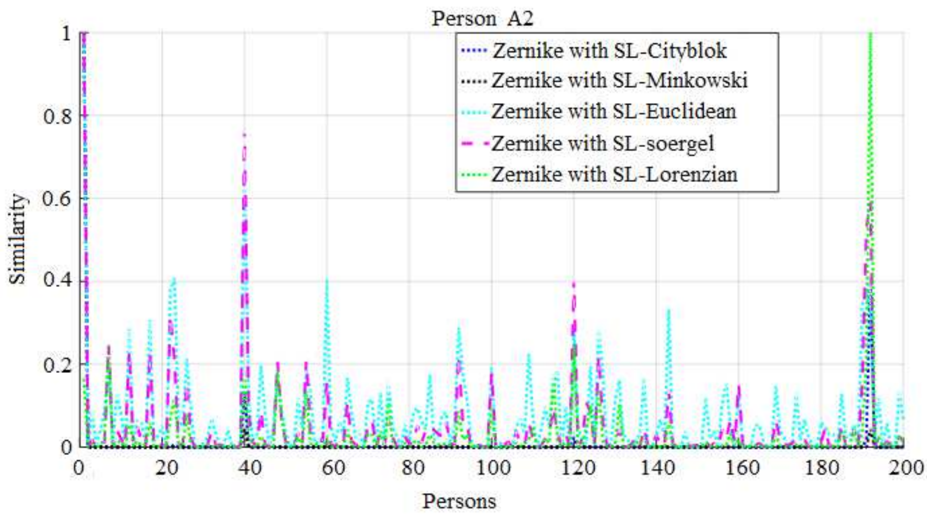
(b)

Fig. 4. Performance under a big change in illumination (a) Above: Gabor filtering with proposed similarity measures (b) Below: Prewitt-Gabor filtering with proposed similarity measures

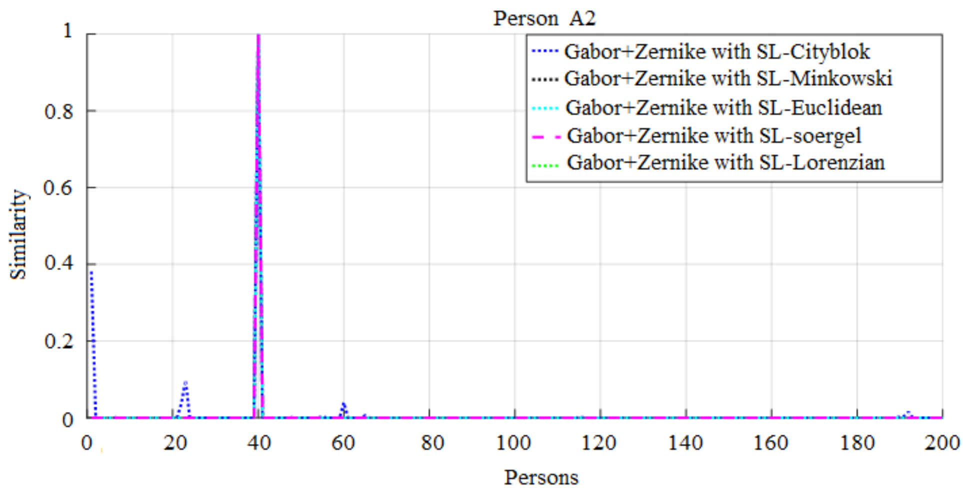


(a)

DOI: 10.3844/ajassp.2017.828.842



(b)



(c)

Fig. 5. Performance under change of pose (a) Above: Gabor (b) Middle: Zernike (c) Below: Gabor-Zernike filtering with proposed similarity measures

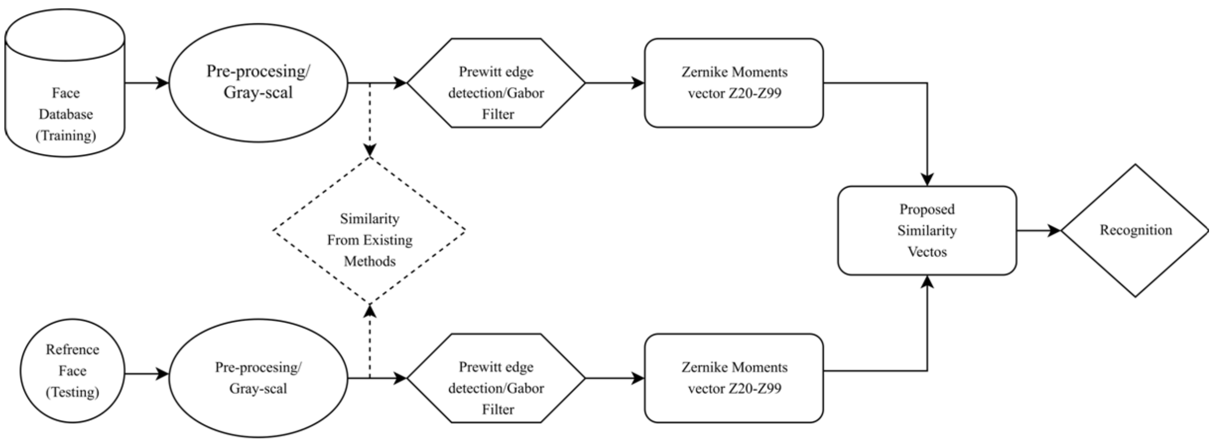


Fig. 6. The proposed recognition process versus comparison methods

DOI: 10.3844/ajassp.2017.828.842

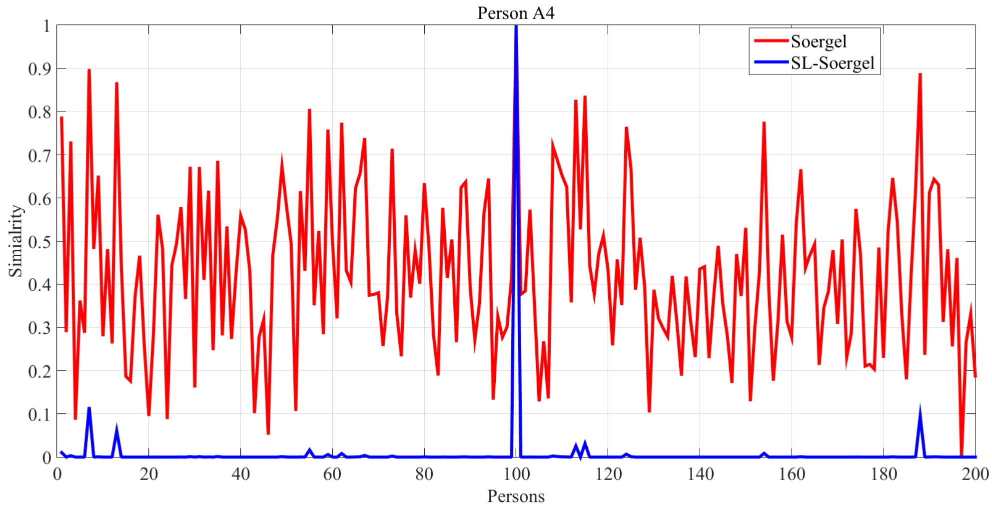


Fig. 7. Soergel metric versus SL-Soergel.

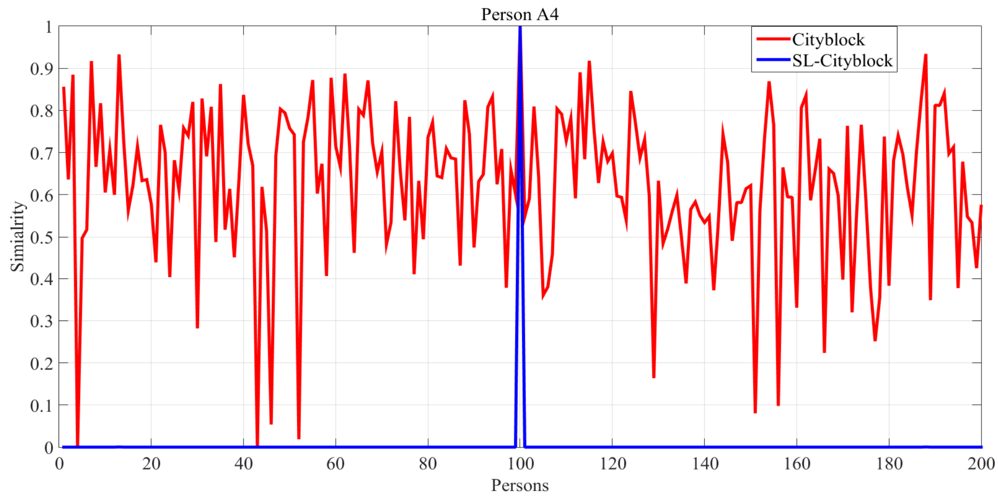


Fig. 8. Cityblock metric vs. SL-Cityblock

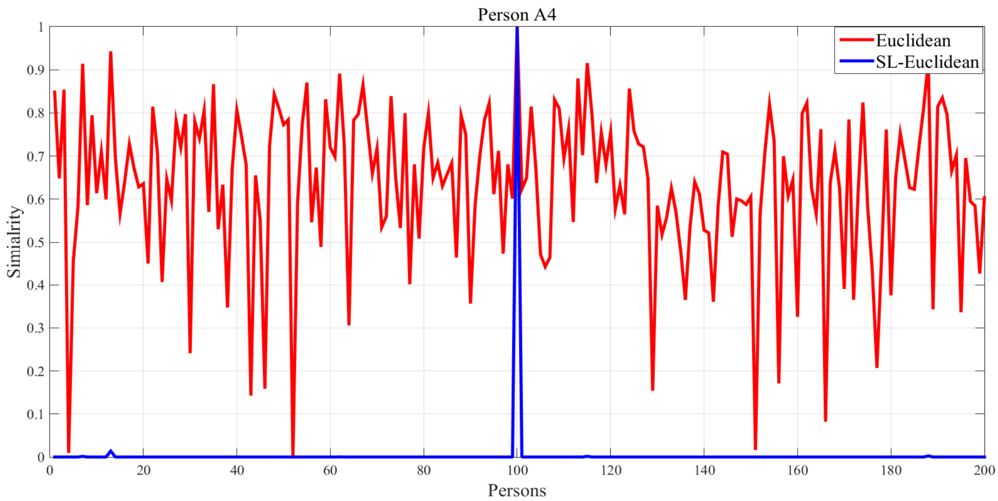


Fig. 9. Euclidean metric versus SL-Euclidean

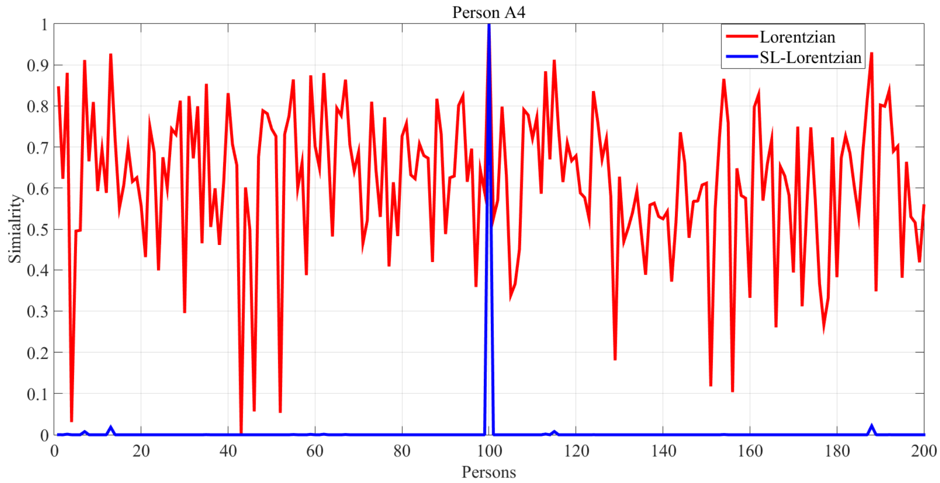


Fig. 10. Lorentzian metric vs. SL-Lorentzian

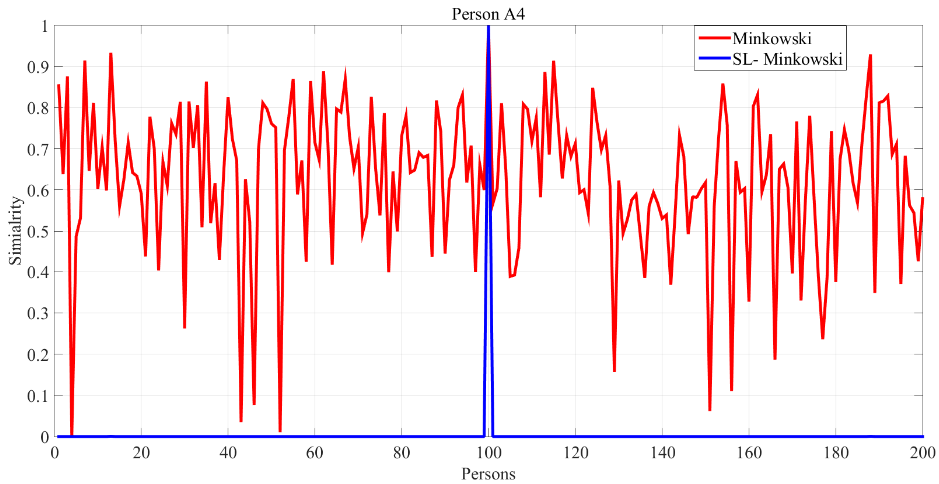
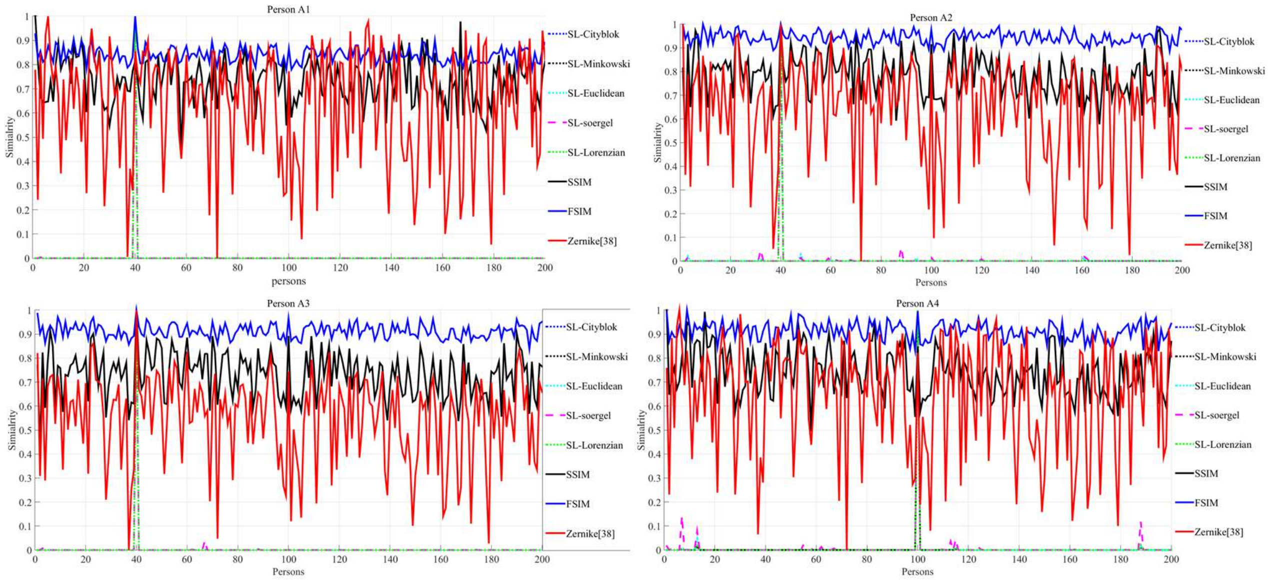


Fig. 11. Minkowski metric versus SL- Minkowski metric



DOI: 10.3844/ajassp.2017.828.842

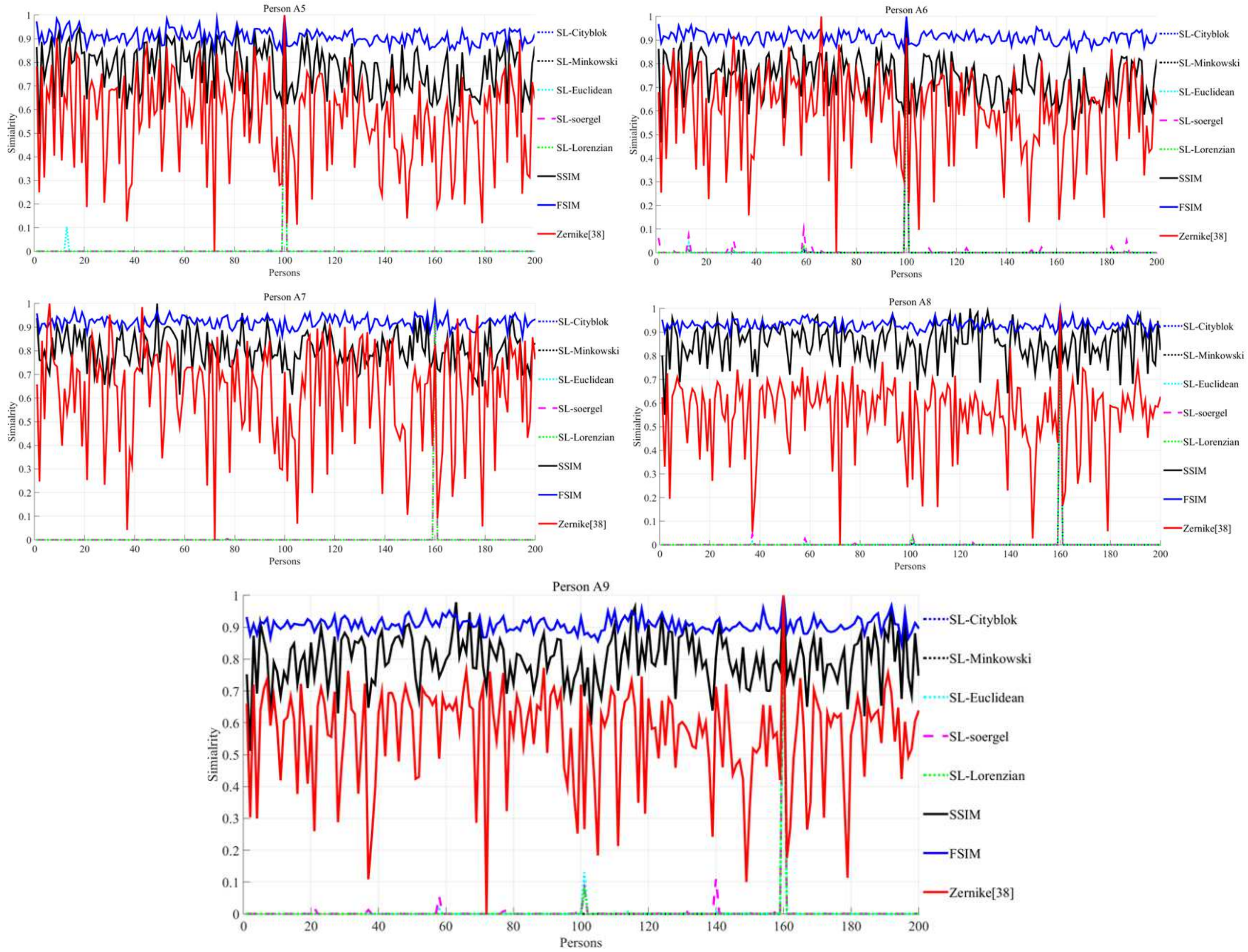
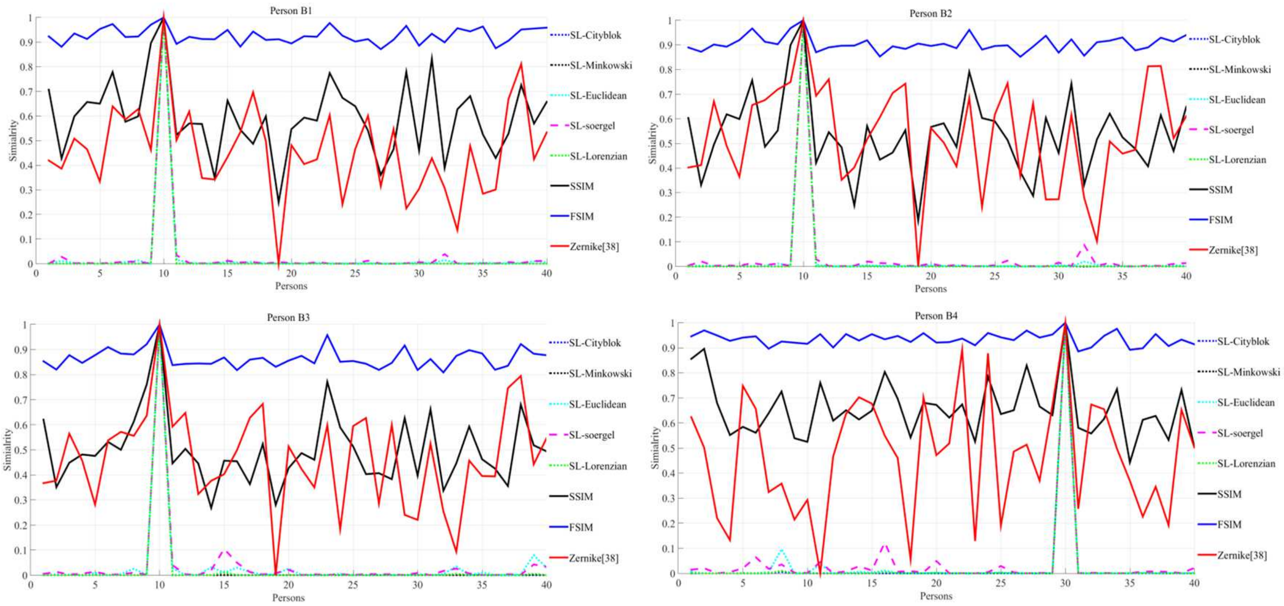


Fig. 12. Schoenberg logarithmic similarity measures versus comparison methods for FEI face database



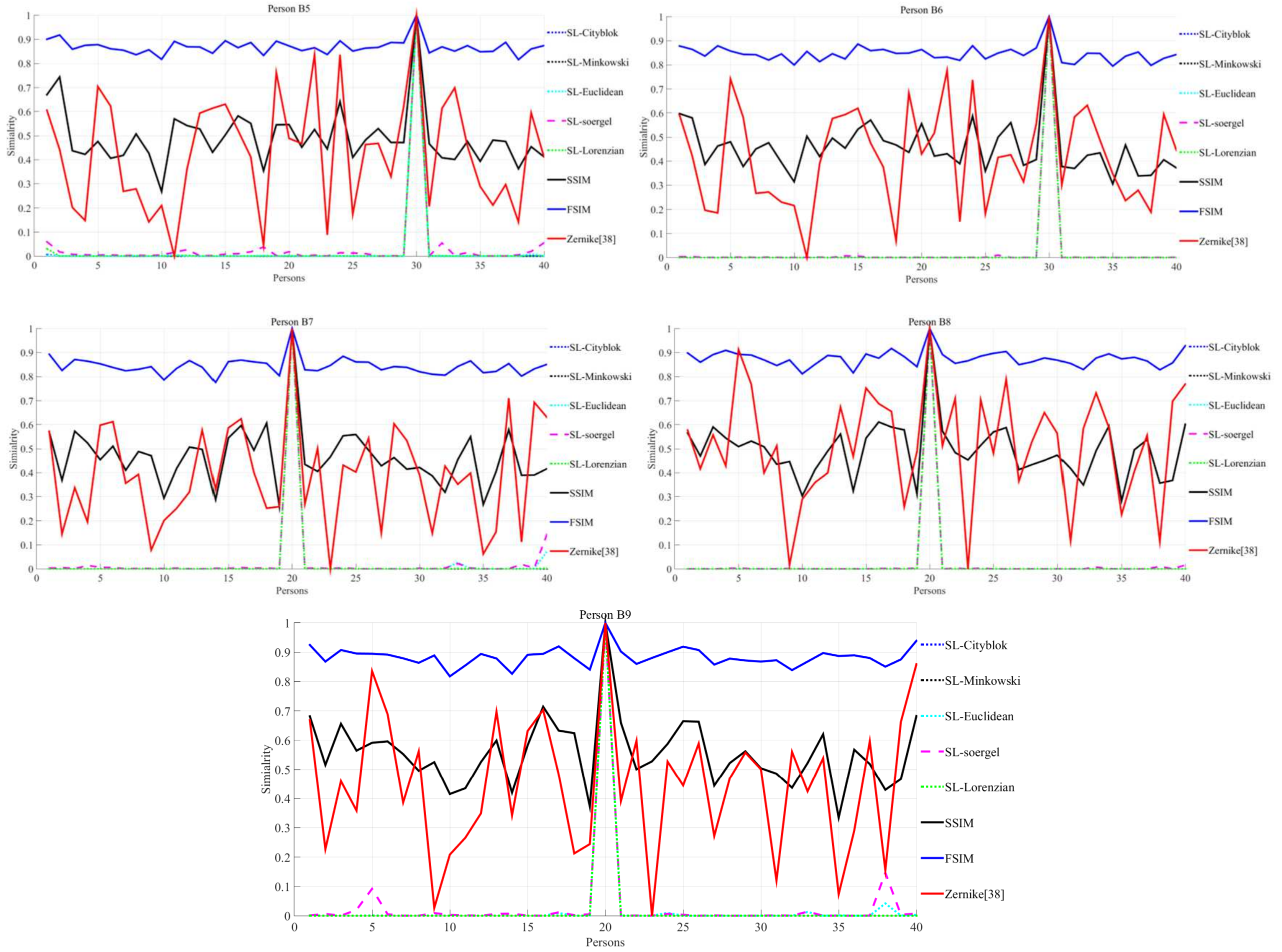


Fig. 13. Schoenberg logarithmic similarity measures vs. other methods for ORL database

Table 1. Recognition rate for proposed method versus other methods

Method	Recognition rate (%) ORL database	FEI database
SSIM	80.0	68
FSIM	90.0	78
Zernike moments (Singh *et al*., 2011)	89.5	85
Proposed method with SL-Minkowski	95.0	94
Proposed method with SL-Lorentzian	97.5	89
Proposed method with SL-Cityblock	97.5	94
Proposed method with SL-Euclidean	92.0	91
Proposed method with SL-Soergel	95.0	92

Table 2. Confidence rate for proposed method versus other methods for FEI database

	Confidence rate (%)								
Method	Person A1	Person A2	Person A3	Person A4	Person A5	Person A6	Person A7	Person A8	Person A9
SSIM	----	1.790	8.46	----	0.0521	10.89	----	1.010	2.130
FSIM	7.48	0.000	1.500	0.43	0.0155	3.52	2.4	1.930	3.210
Zernike (Singh *et al*., 2011)	----	0.390	13.92	----	96.300	----	----	16.70	22.74
SL-Minkowski	99.98	99.90	99.98	99.45	99.980	99.61	99.98	99.98	99.98
SL-Lorentzian	99.96	99.48	99.82	97.84	99.960	97.38	99.98	96.89	91.67
SL-Cityblock	99.98	99.65	99.88	98.50	99.980	98.72	99.98	98.94	100.0
SL-Euclidean	99.92	97.19	99.72	95.30	90.850	95.87	99.98	98.53	86.96
SL-Soergel	99.62	94.40	96.17	85.93	99.990	90.25	99.57	95.51	89.09

Table 3. Confidence rate for proposed method versus other methods for ORL database

	Confidence rate (%)								
Method	Person B1	Person B2	Person B3	Person B4	Person B5	Person B6	Person B7	Person B8	Person B9
SSIM	10.36	10.08	22.86	10.43	25.62	40.26	39.37	38.87	28.57
FSIM	2.23	3.20	4.24	2.43	8.21	11.37	10.71	7.14	6.11
Zernike (Singh *et al*., 2011)	18.83	18.58	20.54	10.80	16.42	22.40	28.96	8.75	14.06
SL-Minkowski	99.99	99.92	99.31	97.37	98.98	99.99	99.03	99.98	99.93
SL-Lorentzian	99.26	98.05	94.18	98.19	95.28	99.99	99.41	99.93	99.98
SL-Cityblock	99.85	99.57	98.50	99.03	98.84	99.95	99.69	99.99	99.97
SL-Euclidean	96.39	95.73	98.52	90.34	98.56	99.90	90.67	99.95	95.81
SL-Soergel	93.47	90.58	90.98	84.04	94.05	99.04	89.11	99.12	85.34

Table 2 and 3 show that the proposed method, in case of correct recognition, provides higher confidence than other measures, where the confidence rate between the wanted person with respect to other different persons is more than 90%. This means that the proposed measures give less suspected candidates in the process of face recognition, which leads to less time investigating un-necessary faces of the database. This time difference means a lot when the database is very large.

Note that global analysis of face has been applied in this study. Attempts to improve performance would be explored in future works by extracting local autocorrelation-like features (Lajevardi and Hussain, 2010b) or hybrid features (Lajevardi and Hussain, 2009a). It is worth noting that local analysis outperforms Gabor filtering in complexity (Lajevardi and Hussain, 2009b).

Conclusion

In this study we presented a novel approach for the face recognition that combines Prewitt edge detection, Gabor filter and Zernike moments in one domain. On this domain, five efficient similarity measures have been used to compute the similarity scores in holistic face recognition using standard face databases (specifically, FEI and ORL databases). The main idea of the proposed measures is to find the distance in the Zernike- Prewitt-Gabor domains of a test image versus a database of images. The classical distance metrics have been modified using the Schoenberg transform to enhance the extraction of similarity. Simulations showed that the proposed similarity metrics outperform classical distance metrics. The performance difference is clearer when face recognition is performed under changes of illumination or pose, where existing methods may fail. The main performance criteria used in this study were the correct recognition rate and recognition confidence, defined as the similarity difference between the best match and the second-best match in the database.

Acknowledgment

The Authors would like to thank Edith Cowan University (Australia) and the Ministry of Higher Education and Scientific Research (Iraq) for supporting this project.

Author's Contributions

Ahmed Jebur Ali: Design and simulation of the proposed measures. He also contributed to writing and testing the proposed measure on AT&T and FEI databases.

Zahir M. Hussain: Supervisor of the project, contributed to the design and simulation of the proposed measures. He also contributed to writing.

Mohammed Sahib Mechee: Contributed to mathematical analysis of the proposed measures. He also contributed to proof-reading and final presentation.

Zainab Ali Khalaf: Contributed to mathematical analysis and check-up of the codes of the proposed measures. She also contributed to testing the measures versus existing ones.

Ethics

The Authors declare that there are no conflict of interest or ethical issues associated with this work.

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