Multi-Modal Biometrics Fusion Based on Component Analysis and Stationery Wavelet Transform

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Abstract—It has been observed that the accuracy of multimodal biometric system is highly dependent on the adequacy of the applied fusion technique. Fusion at sample, template, matching and ranking levels have all proved reasonable contributions to the performance of the multi-modal systems. In this paper, a model that is based on the combination of Principal Component Analysis (PCA) and Stationary Wavelet Transform (SWT) is proposed for the fusion of biometric images. The model comprises image depuration, histogram balancing, pruning and homogenization as well as PCA-based feature extraction stages. The decomposition and fusion of the images (using the extracted features) were based on SWT. The experimental study of the model with standard face and ear images revealed its suitability for obtaining high quality fusion. The obtained Peak Signal to Noise Ratio (PSNR), Mean Square Error (MSE) and Standard Deviation (SD) values established the superiority of the proposed model over some related ones.

Keywords—Multimodal biometrics, face, ear, biometric fusion, filtering, PCA, SWT.

1. Introduction

Biometric means life measurement and it focuses on attaining accurate measurement of individuals' un g ique biological and behavioral traits with a view to safely and reliably presents them for computer or other electronic system representations and identity management. While physiological measurements are classified into fingerprints, retinal and iris, face, ear, nose and deoxyribonucleic acid (DNA), behavioral measurements are grouped into gait, signature and voice [1], [2], [3], [4]. These characteristics are measured and translated into a feature set which is often compared against the template set in human identity verification or authentication [5], [6], [7].

Biometric-based identity management is noted for strength of uniqueness, permanence, measurability and individuality and its increasing popularity has been attributed to existing array of sign-on applications and devices [3]. A biometric system uses any or combination of the characteristics for an individual to establish uniqueness based on combination of hardware and pattern recognition algorithms [8]. Biometrics eliminate card mobility and information (password, pin or username) memorization and also serve as very good substitutes to possession-based techniques (key and token) which are susceptible to sharing, misplacement, duplication, lost and theft.

Biometrics technology has offered a quantifiable solution to undocumented and uncontrolled access, identity card transfer or swapping, manual badge checks, credential reshuffle and replacements and the likes. Biometric technology is simple, accurate, cost-proven and reliable in view of its resistance to misplacement, forgetfulness, guessing and forgery [9], [10], [11], [12]. The successful implementation of biometric systems requires addressing a number of issues, including accuracy, efficiency, robustness, applicability and universality [13]. Unimodal biometric system is based on a single modality such as the face, fingerprint and so on. Such a system is synonymous with the problems of noising data, intra-class variations, inter-class similarities, non-universality, spoof attacks, high error rates and non-invariant representation arising from varied interactions of the user with the sensor [6], [14], [15].

Multimodal biometric systems employ two or more biometric modes to improve the systems performance, raise the scope, discourage spoofing and promote indexing. Improved performance has been noticed with uncorrelated traits and integration of parameters that are user specific in multimodal systems. Without doubt, the widespread deployment of multimodal biometric systems in government and private establishments across the world has offered more secured and reliable human identity management [4]. Multimodal biometric systems enjoy comparative advantages over unimodal systems and hence, are more popular. They are very difficult for intruders to manipulate in view of their indexing on multiple evidences of the same identity as a viable approach to eliminating the problems inherent to unimodal biometric systems [5], [9], [16], [17].

The existing multimodal biometrics fusion scenarios depend on the number of traits, sensors and feature sets and are classified into single biometric trait, multiple sensors; single biometric trait, multiple classifiers; single biometric trait, multiple units and multiple biometric traits [18], [19], [20], [21], [22], [23], [24], [25], [26], [27]. Existing biometrics fusion algorithms include Score Normalization, Minimum Average Correlation Energy Filter, Neyman-Pearson (Product) Rule and Gaussian Copla Models, Principal Components Analysis (PCA), Fisher's Linear Discriminate Methods and Geometry Preserving Projection [23], [24], [25], [26], [27], [28], [29], [30], [31], [32]. A multimodal biometric system may operate in serial, parallel or hierarchical mode and fusion at the feature and matching score levels are the two major integration strategies [13], [33], [34]. Section II of this paper presents the related work while Sections III and IV present the proposed model and experimental study respectively. The conclusion drawn is presented in Section V.

2. Related Works

The authors in [35] proposed a multimodal biometric system that is based on score level fusion of fingerprint, iris and ear features. The system yields improved recognition accuracy but suffers spectral degradation, color distortion and significance damage to the image contrast thereby unsuitable for real time applications. In [36], a multimodal biometric system that combined face and iris features for improved identity verification was developed. The system is based on determination and comparison of un-weighted or weighted sum from the two modalities. Based on the matching distances, Fisher's Discriminant Analysis (FDA) and a Neural Network (NN) with Radial Basis Function (RBF) were used to classify face and iris into genuine or impostor feature vector. Although the system enhanced verification accuracy, it is prone to increased Signal to Noise Ratio (SNR) and degraded fused image due to its weighted sum rule.

The authors in [37] proposed a system that is based on the fusion of face and fingerprint features for human identity management. The matching for the two modalities is based on Support Vector Machines (SVM) classifier and fusion is performed at the matching score level. The system addresses the problems of noisy sensor data, non-universality, non-distinctiveness and spoof attack common to unimodal system but it is limited by increasing SNR of the fused image and relatively high Equal Error Rate (EER). A multimodal biometric system that uses face and ear features and comprises training and recognition phases is proposed in [38]. At the recognition phase, fuzzy-based authorization is preceded with shape and texture features extraction from the face and ear images based on modified region growing algorithm and Local Gabor XOR Pattern (LGXP) technique respectively. The system offers improved recognition rates and greater performance accuracy compared to some existing systems but the shape and texture features are not devoid of noise and some irregularities.

With a view to improving on the accuracy of multimodal biometric systems, the authors in [39] proposed ear and profile face fusion for minimum distance classifier recognition. Log-Gabor of the features of the two modes were extracted and integrated into a combined feature which is then mapped to kernel space to acquired stronger discriminant feature set that is presented for Kernel Fisher Discriminant Analysis (KFDA) classification. The system performance depends on parameters like orientation and scale bandwidths and minimum scale wavelength in addition to its computational complexity and low speed.

The authors in [40] proposed SWT and second generation Curvelet transform based algorithm for biometrics image fusion. The source images were decomposed using SWT transform while the high and low frequency components were respectively acquired, after which the low frequency components were fused using Curvelet transform while the high frequency components were fused based on the largest absolute value coefficients. The inverse SWT was used to get the final fused image. The algorithm preserves the advantages of the spatial and frequency domain techniques, retains edges and effectively checked wavelet transform fusion induced block effect. The performance index and visual effects showed the superiority of the algorithm over single application of SWT or Curvelet algorithm.

3. Proposed Model

The proposed model is conceptualized in Figure 1 and comprises of stages for image enhancement, PCA-based extraction and SWT-based fusion.

3.1. Image Enhancement

Image enhancement is used for the purging of extraneous information, recuperation and amplification of helpful information as well as moving out entire generalization of the attribute set. It involves image histogram balancing, determination of the areas of significance (AOS), pruning and homogenization as well as image depuration.

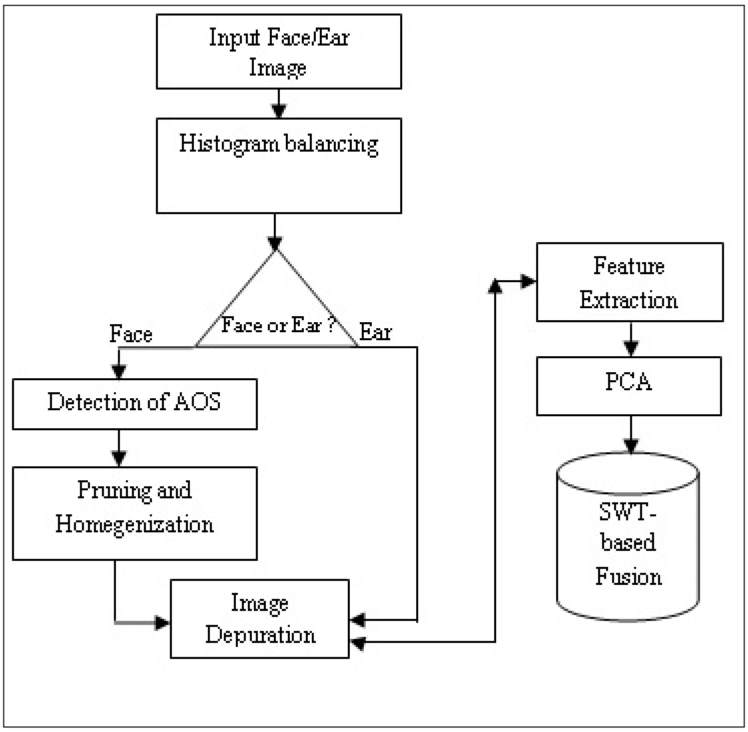

Fig. 1. Conceptual representation of the proposed system.

3.1..1 Histogram Balancing

Numerous biometric images are often weakly contrasted with spurious attributes and artefacts that render them useless for any meaningful ocular scrutiny. Histogram balancing is consequently performed towards elevating the active collection of the image intensities (gray levels) for enhanced optical disparity and regular histogram for all intensity values. If P(a,b) is the image with distinct y gray values, the histogram is represented by the possibility β_l of the incidence of the gray level P as follows:

$$\beta_1 = \frac{x_l}{S} \tag{1}$$

l=0,1,...,t-1, x_l is the grey point assessment for pixel 1 and S is the addition of all pixels in the image. The computed figures for the output image Ω_l are in the range [0,1] and is derived from:

$$\mathbf{\Omega_1} = \frac{x_l}{S} \tag{2}$$

3.1..2 Determining the areas of significance (AOS) in Face Images

The AOS is the known margins on the image and its computation is based on the creation of a twofold pretence of the equal magnitude with the template image. The AOS pixels are put at value 1 while every other pixel is put at 0.

3.1..3 Pruning and Homogenization in Face Images

The conspicuous discrepancy in magnitude and form of face images establishes substantial coercion to the development of a multiple mode biometric scheme. This discrepancy is solved via the pruning of the images into smallest rectangles of same dimensions (v, w) as follows:

$$\mathbf{v} = c_1 t + c_2 u + c_3 \tag{3}$$

$$\mathbf{w} = d_1 t + d_2 u + d_3 \tag{4}$$

t and u are the pixel coordinates and c_1, c_2,c_3, d_1, d_2 and d_3 are real-valued estimates

3.1..4 Image Depuration

The biometric images were derived from the photo electronic digital camera that subjects them to dirt and unauthentic gap effects in curves or outline. To determine the extent of these effects, a uni-directional depuration algorithm is used on the (t, u) pixel point in the ear and face images as follows:

$$\mathbf{D}(\mathbf{t}, \mathbf{u}) = \frac{1}{2\pi\sigma^2 e^{\frac{t^2+u^2}{2\sigma^2}}} \tag{5}$$

σ is the average departure of the image gray scale estimates.

3.2. PCA-Based Feature Extraction

The ear and face feature extraction is based on PCA and it involves dimensionality reduction and feature selection and extraction. Dimensionality reduction is used to train the PCA with a view to generating the eigenvectors while the mean training image is computed by representing the image as 1-Dimensional vector derived from the concatenation of each row (or column) into a long thin vector. Given M set of sample images of size N by M with training set, T_1 T_2,...,T_S; the mean image,I_μ is calculated as:

$$\mathbf{I}_\mu = \frac{1}{S}\sum_{i=1}^{S} T_i \tag{6}$$

A new image Φ_i with reduced dimension is obtained as follows:

$$\mathbf{\Phi_i} = T_i - I_\mu, i = 1, 2, \ldots, S \tag{7}$$

Image Φ_i is subjected to PCA to obtain a set of orthonormal vectors U_k based on the choice of k^{th} vector as follows:

$$\mathbf{U_k^\varphi} = (\frac{\omega_k}{T_i} - I_\mu) \tag{8}$$

φ is the transformation index, ω_k is the transformation constant for vector U_k and k = 1,2... M. The eigenvalue λ_k feature set is obtained as follows:

$$\lambda_\mathbf{k} = \frac{1}{M}\sum_{i=1}^{M}(U_k^\varphi \Phi_i)^2 \tag{9}$$

The fusion of the images is based on a 2-D SWT decomposition Row and Column scheme that is conceptualized in Figure 2.

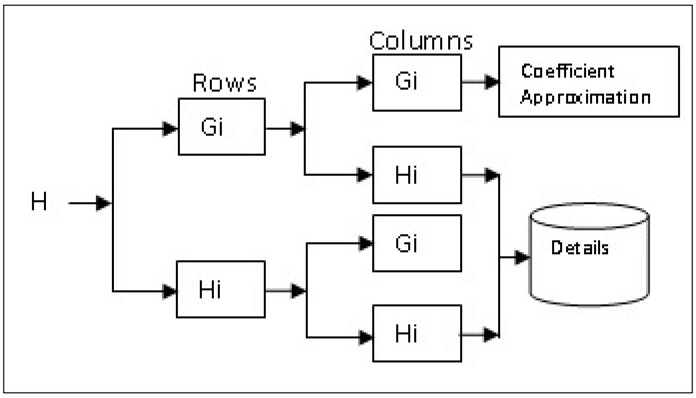

Fig. 2. SWT Decomposition Scheme

The fusion of the extracted feature sets for the face and ear images is based on the decomposition of the feature sets, λ_k into frequency domain using SWT which results in approximate, vertical, horizontal and diagonal images represented as A, V,H and D respectively (shown in Figure 3).

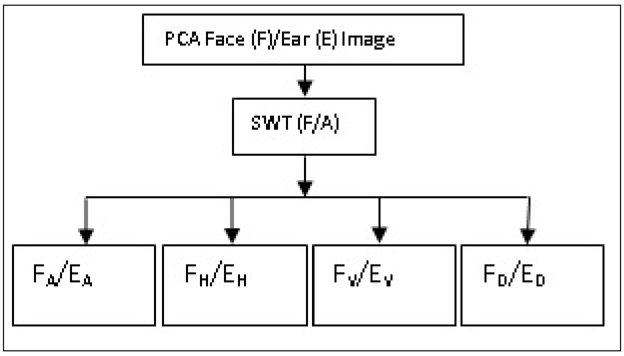

Fig. 3. Decomposition of the PCA face and ear

Component A was derived from low frequency information and it is half the resolution of the original image while V, H and D were derived from vertical, horizontal and diagonal information in high frequency respectively. The coefficients of the approximate I_a, horinzontal I_h), vertical I_v and diagonal I_d components of the fusion of the face and ear images are presented as follows:

$$\mathbf{I_a} = F_A E_A \tag{10}$$

$$\mathbf{I_h} = F_H E_H \tag{11}$$

$$\mathbf{I_v} = F_V E_V \tag{12}$$

$$\mathbf{I_d} = F_D E_D \tag{13}$$

F_A is the approximate image of the Face, F_H, F_V and F_D are the details of the Face while E_A is the approximate image of the Ear, E_H, E_V and E_D are the details of the Ear image. The resultant coefficient C_R is derived from the fusion of the individual coefficients as follows:

$$\mathbf{C_R} = I_a I_h I_v I_d \tag{14}$$

The inverse of the stationary wavelet transform of C_R represents the fused image.

4. Experimental Study

The experimental study of the proposed model was carried out on a Personal Computer with Intel (R) Core ™ i5 – 4200M CPU @ 2.50 GHz processor on 4GB Random Access Memory (RAM). Matlab Version R2013a and MySQL provided the frontend and backend supports respectively on Microsoft Windows 10 operating system environment. Standard and benchmarked face and ear databases obtained from the Federal Executive Institute (FEI) and Mathematical Analysis of Images (AMI) respectively formed the experimental datasets. The face database contains images taken between June 2005 and March 2006 at the Artificial Intelligence Laboratory in São Paulo, Brazil and comprises of 2800 multi-colour and homogeneous background images. Using photo electronic-based digital camera, fourteen (14) facial images were obtained from each of the two hundred (200) individuals using a scale of 10% and 640 x 480 pixel sizes. The ear images in the AMI Database comprise 700 images arising from a set of six right and one left ear images enrolled from each of 100 different staff and students of the Universidad de Las Palmas de Gran Canaria (ULPGC), Las Palmas, Spain in indoor environment using a Nikon D100 camera, under the same settings, lightening and resolution of 492 x 702 pixels in jpeg format.

The histogram balancing experiment was used to alter the histogram of the input image with a view to producing image that exhibits uniform histogram with equally distributed pixel intensities for quality improvement and effective feature detection. Pruning of the AOS of the face image covers the eyes, nose, mouth, cheek and forehead while other parts were completely left out. The ear images were not cropped to avoid losing vital feature points. Histogram balanced results for some selected face and ear images are shown in Figure 4. Figure 5 also presents the detected AOS for some images. Visual inspection of the depurated and pruned face image shown in Figure 4 reveals positive impact of the depuration algorithm on the pruned face image and histogram balanced ear image.

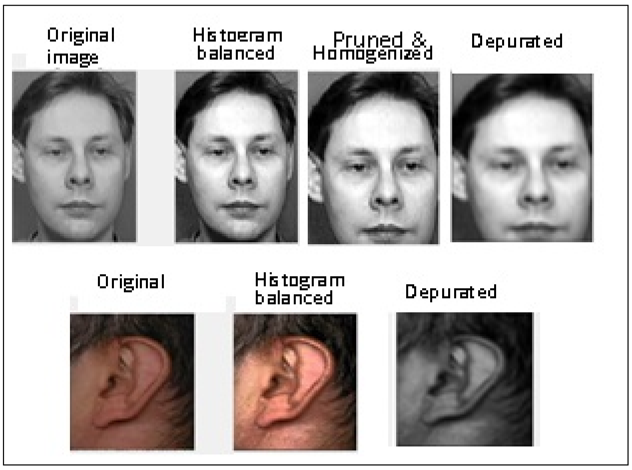

Fig. 4. Decomposition of the PCA face and ear

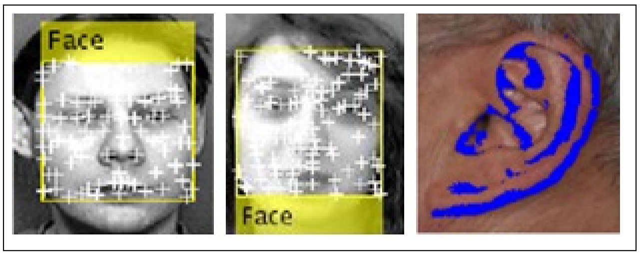

Fig. 5. Detected AOS for selected images

More often than not, features in a biometric image are correlated and simply removing the correlated features may lead to exclusion of some vital information. On this note, PCA-based orthogonal transformation of the complete feature space of the images was performed such that the underlying uncorrelated features are obtained by generating the covariance matrix of the feature values of the face (640x480) and ear (492x702) dimensional vector space as follows:

$$\mathbf{X} - \mu = \begin{pmatrix} (x_1^1 - \mu \; . \; . \; . \; x_d^1 - \mu \\ . \\ . \\ . \\ x_1^N - \mu \; . \; . \; . \; x_d^N - \mu) \end{pmatrix} \tag{15}$$

$$\mu = \frac{1}{N} \sum_{i=1}^{N} x^i \tag{16}$$

N and d are the row and column dimensional values respectively.

The orthogonal transformation led to reconstructed images with direction of maximum variance in a smaller dimensional feature subspace that retains most significant information. The covariance matrix of the PCA images is diagonal, meaning that the new axes are uncorrelated having rotated the axes of the n-dimensional space. The eigenvalues of the same covariance matrix were used to obtain the eigenvectors of the covariance matrix which was in turn used to obtain the new features of the original images as a linear combination. The obtained re-constructed images of some selected images are presented in Figure 6.

Fig. 6. PCA Face and Ear images

The reconstructed images were subsequently transformed into frequency domain for Stationary Wavelet Transform (SWT)-based fusion. The transformation is based on decomposition of the images into approximate, vertical, horizontal and diagonal components which are at half the resolution and same size as the original image. Figure 7 shows an experimentally obtained reconstructed image and its decomposition.

Fig. 7. SWT Decomposition

The face components images are represented by F_d, F_v, F_h and F_a while the ear components images are represented by E_d, E_v, E_h and E_a. a means application of low pass filter along rows before low pass filter along columns while h means application of high-pass filter along rows and then low-pass filter along columns. Similarly, v implies a low pass filter along rows followed by a high pass filter along the columns and d indicates a high-pass filter on the rows and then a high-pass filter along columns. The four components of the face and ear images are fused to obtain single representation some of which are demonstrated in Figure 8.

The performance of the fusion model was measured based on PSNR, MSE and SD. PSNR presents the peak error and the quality measurement between the original and fused representation with higher values depicting better quality, compression and reconstruction and it is obtained from:

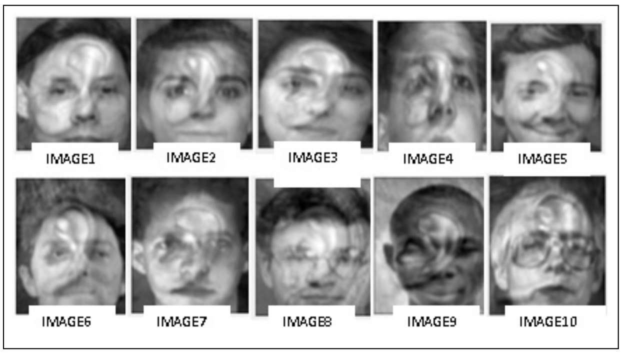

Fig. 8. Samples of fused Images

$$\mathbf{PNSR} = 20log\frac{255\sqrt{3mn}}{\sum_{i=1}^{m}(A_{ij}-B_{ij})^2} \tag{17}$$

A is the original image, B is the fused image, i is pixel row index, j is pixel column index and m, n are the number of rows and columns. MSE represents the cumulative squared error for the original images and their fused representations with lower values indicating lower errors and better performances. It is obtained as follows:

$$\mathbf{MSE} = \frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n}(A_{ij}-B_{ij})^2 \tag{18}$$

The SD values are measures of the contrast in the fused representation with higher value showing higher quality and it is calculated based on the Equation:

$$\rho = \frac{1}{mn}\sum_{i=1}^{n}(x-\mu)^2 \tag{19}$$

Figure 9, Figure 10 and Figure 11 present the graph of the obtained PNSR, MSE and SD respectively. Table 1 shows the comparative analysis of the findings from the current work with those from some existing and related works. The superiority of the proposed model for the three standard metrics is demonstrated.

TABLE 1
Comparative Analysis with other Research Works

Research	Fusion Model	PSNR	MSE	STD	Output
Chaunte et al., 2010 [41]	DWT, and GA	High	Low	High	Translation Invariance and poor spatial resolution
Monwar. M., 2012 [14]	Markov Chain	Low	High	High	Rank level fusion with less accuracy compared to match level fusion
Nair et al., 2013 [42]	DWT , DCT + PCA	Low	High	High	Poor spatial quality fused image with DWT translation invariance
Mirajkar & Sachin , 2013 [43]	SWT	Low	High	High	Degraded image with Poor spatial resolution
Poornima, 2013 [44]	PCA+ Euclidean distance	High	Low	Low	Results in spectral degradation and colour distortion
Sheetal & Rajender, 2015 [45]	Min-max normalization and SSR	Low	High	High	Poor spatial resolution and spectral content
Devinder, 2016 [46]	SWT+PCA	High	Low	High	Poor spatial resolution
Tilak, 2016 [47]	SWT+PCA	High	Low	Low	Eigen features were used for fusion.
Amandeep & Reecha, 2016 [48]	SWT + Particle Swarm Optimization	High	Low	Low	Poor spatial resolution. PCA+SWT outperform SWT only
Current Research	PCA+SWT	Very High	Very Low	Very Low	Good spatial and spectral content

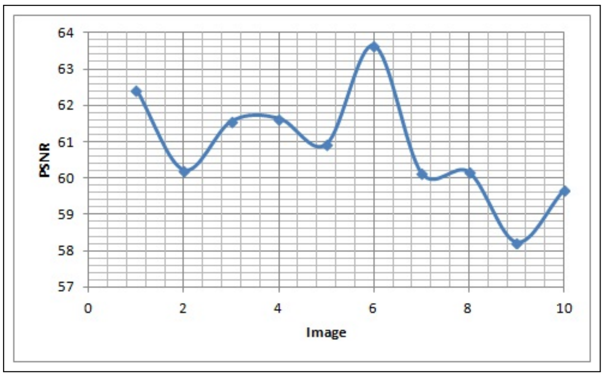

Fig. 9. PNSR values for fused images

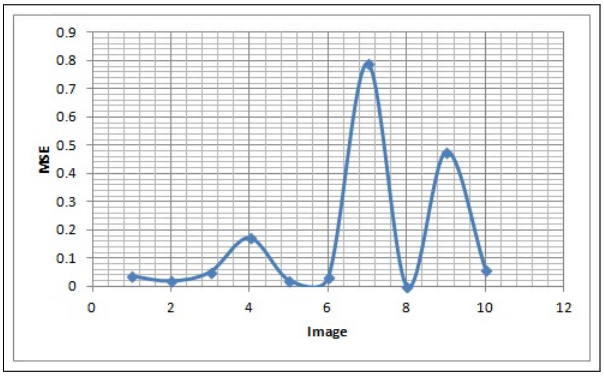

Fig. 10. MSE values for fused images

5. Conclusion

A principal component analysis and stationery wavelet transform-based model for multi-modal biometrics fusion has been presented. The research established the integration of the two techniques as a viable option to fusion in multi-modal biometric applications. While the existing works respectively present techniques for fusion of a combination of two or more of fingerprint, iris, ear, nose and face, this research emphasised on the fusion of ear and face images. The application of very high spatial resolution and significantly improved spectral quality content for resultant feature-induced multimodal biometric fusion is also demonstrated. Furthermore, the possibility and efficacy of the integral method for overcoming some of the challenges confronting commonly known techniques for multi-modal bio-

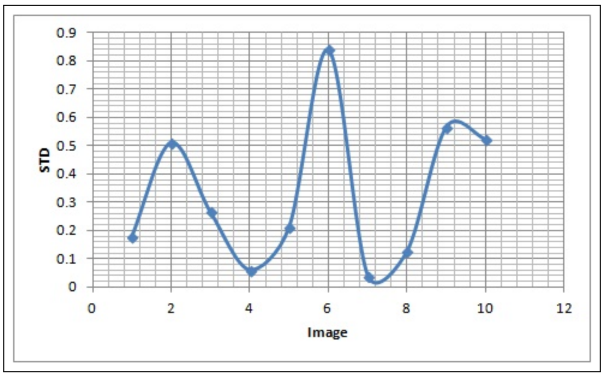

Fig. 11. The STD values for fused images

metric fusion is advanced. These challenges include non-compliant with real-time applications, high signal to noise ratio, high equal error rates, non-resistance to noise and structure irregularities, parameter dependency, computational complexities and low operational speed. Analysis of the obtained values for standard metrics such as PSNR, MSE and STD from the experimental study of the model on benchmarked face and ear databases revealed how the proposed model extensively addressed the aforementioned challenges. The model also provides a foundation for a once-off extraction of features from multi-modal biometrics as against the serial or parallel feature extraction modes that are repetitive and resource (processor time, space) intensive. While the research emphasised the expediency of the integration of principal component analysis and stationery wavelet transforms for synthesis of multi-modal biometrics, existing literature leveraged on assortment of techniques. These techniques include discrete wavelet transform, genetic algorithm, Markov chain, Euclidean distance, normalization, simple sum rule (SSR), particle swarm optimization and score level. Others are weighted sum, Fisher's discriminant analysis, neural network, fuzzy logic and support vector machine. The PSNR recorded for the existing literature (techniques) range from 'Low' to 'High' as against 'Very High' that is obtained for the study. The study also recorded lowest MSE and STD values compared to what obtained for the existing techniques, which indicates better performance and greater precision of the principal component analysis and stationery wavelet transform centric model. Furthermore, the existing techniques are predisposed to translation invariance, poor spatial resolution, colour distortion and diminishing performances, which retards their suitability for real-time multi-modal applications. The proposed model on its own recorded good spatial and spectral content as established by the PSNR, MSE and STD values, and hence, more suitable for multi-modal applications. It is pertinent to state that the new model is susceptible to degrading performances when the image quality is extremely poor or massively contaminated as accuracy level and accessible information in the processed image are adversely affected. Future research will therefore focus on re-engineering the model for better performance on poor quality images as well as improving on the signal-to-noise ratio.

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