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Robust Analysis of Multimodal Biometric Verification System Under Various Spatial Noise Conditions

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***Abstract*—** Instinctive person verification system still faces various challenges in desirable performance due to dependent and independent noise. Most of the physiological biometric modalities are 2-D images, which may have high probability to get affected from noise. This work proposes a comprehensive analysis of robustness of various unimodal and multimodal biometric systems in clean and noisy conditions. On each stage of biometric system we emphasize, feature extraction, level of fusion and suitable normalization schemes. For feature extraction, methods we have employed subspace, kernel and texture based methods and we have subjected the data on all four levels of fusion schemes- sensor, feature, match score and decision level. The objective of this paper is to analyze the robustness of unimodal systems with distinct modalities and evaluate the robustness of a multimodal system with combinations of two, three and four modalities at different levels. All the experiments were evaluated for both clean and noisy data with virtually generated noises of Gaussian and Salt & Pepper methods, and were applied on all biometrics modalities considered for experimentation. The synthetic multimodal database was prepared from standard database of Face, Palmprint, Finger knuckleprint and Handvein. The obtained results and observations in terms of GAR (Genuine Acceptance Rate) show that palmprint with LPQ features are most effective in unimodal systems. In case of multimodal systems, combination of Face (KICA) and Palmprint (LPQ) are most beneficial. This work also suggests some important guidelines on selection of suitable biometric modality, feature extraction algorithms and fusion scheme.

***Keywords*—**Robustness, Noise, Subspace, Multimodal, Biometric.

I. INTRODUCTION

The world population is experiencing growth by almost three to four humans per second that makes unique identification of individuals of great impact relying on physiological and behavioral characteristics they possess. Understanding the human physical and behavioral activities influenced by brain waves triggered by external stimuli like body temperature, electrocephalogram, odour sensing, electromyography and many other metrics can be measured deploying varieties of sensors and devices. Managing the central data repository that captures, processes, accesses and evolves exponentially with huge amount of unstructured data is onerous task. The high demand from the traits employed finds application widely in deploying biometrics in ATM, gender classification, crime regulations, physical and logical access control, law enforcement, security surveillance etc.

The automated biometric authentication system gets inputs from the raw physiological and behavioral traits which exhibits unique and ample characteristics such as universality, permanence, measurability, acceptability and circumvention on each individual globally that extracts the set of features on applying suitable feature extraction techniques. Then the classifier is trained efficiently to predefined classes and the matching takes place in verifying the claimed identity. The right decision while matching is done by fixing up threshold in performing the identification **1:N** i.e. whether the claimed identity is familiar to the system or by the verification **1:1** i.e. checking the authentic user from his/her claim. The performance of the system is appraised by the measures that exhibit trade-off between false acceptance rate (FAR) and false rejection rate (FRR). The authentication system with lower equal error rate (EER) and high GAR are desirable. Stages comprising of biometric authentication system include 1) pre-processing stage which involves improving the raw biometric data obtained from the sensor and may involve normalization, Region of interest (ROI) extraction and filtering etc. 2) Feature extraction stage includes highlighting the most discriminating portion of the image and relying on various feature extraction techniques like Template Matching Approach, Appearance-Based Approach, Kernel methods and Texture methods. 3) Matching module computes the similarity and dissimilarity of the testing image feature values with already stored feature template present in the database generating a matching score [18]. 4) The Decision module decides whether the claimed identity is accepted or rejected based on the match score analysis [1].

Dealing with imperfect data like distortion, disturbance which results in system degradation is a great challenge in real world data. The suitable feature extraction algorithms and robust learnt classifiers that avoid over fitting of noisy data, should be chosen in handling the system trained with clean data, whereas the noisy data hinders the knowledge retrieval. Tailoring the deployed system productively for all the classes considered is a key requirement [2]. Image noise is unenviable spurious information congregated by photo electronic, impulse, structured types of noises [13]. The biometric system involving only one trait in its authentication process is more likely to get spoofed due to the factors such as noisy data, spoofing, and non-universality, inter-class similarity. To address these limitations multimodal system should be incorporated acquiring more than one biological or behavioral modalities that exhibit the properties such as universality, distinctiveness, permanence, collectability, performance and circumvention in improving the success rate of identification and verification significantly. While considering multimodal biometric systems, challenges arise [4] such as how many modalities and which kind of modalities are essential for the deploying system? Which modalities to fuse? Which level of fusion gives best accuracy?

This paper tries to specify most efficient and robust biometric modality type with respect to clean and noise corrupted images. The work also provides most suitable discriminating feature extraction algorithm for specific levels of noise. Moreover, best possible fusion combinations of various image modalities along with appropriate fusion strategies for them are also explored in this paper. It is aimed that this paper will assist Biometric authentication systems in selecting appropriate combination of modalities and number of modalities to be fuse for multimodal identification in real-time.

The remaining of the paper is organized as follows: section II review of related work on different robust multimodal systems. Section III give detail of proposed work; section IV describes various methods and algorithms employed in this work. Section V discuss the experimental results obtained and the conclusion is drawn in section VI.

II. LITERATURE REVIEW

Stanislav Pyatykh et al. [10] proposed estimation of noise techniques employing principal component analysis on the image blocks which is outstanding in performance. They have assumed the Gaussian noise for their experiments and addressed the images that contains mostly textures by estimating the variance in noisy image, even if there is no homogeneous areas. P. Kartik et al. [11] describe robust multimodal authentication system based on facial features extracted from subspace methods, speech recognition is done using Mel Frequency Cepstral Coefficients (MFCC) and signature system is developed using horizontal and vertical projection profiles and DCT features are used in proposing this recognition system. The system is developed using score level fusion under sum rule. Inducing the salt and pepper noise densities at varied levels the unimodal and multimodal system was subjected to performance measures, where the multimodal system yielded 95% of accuracy though all the traits were corrupted with noise and it substantially outer performed than the unimodal system.

J.A. Sáez, et al [12] proposed a novel part in estimating the behaviour of classifiers against the noisy data with the Equalized Loss of Accuracy (ELA) considering the class noise type error or labelling error. The role of a classifier is very much indeed in governing a system’s accuracy, how well the classifiers are trained with the controlled noisy constraints matters. D. F. Nettleton et al. [14] proposed a systematic work in analysing attribute noise and class noise and how the learning algorithms tackle the real time data effectively under noisy conditions. Category 1, contains of the Naïve Bayes probabilistic classifier and C4.5 tree induction, and category 2 set contains the IBK instance-based classifier and the SMO support vector machine. NB outer performed than the other algorithms and SMO shows poor performance.

Madhu S. Nair et al. [15] proposed a decision based algorithm for the removal of salt and pepper noise in gray level and color images, the noisy pixel in the image is replaced either by median or mean value from the previously processed pixel value phase which retains the smooth transition among the pixels and achieves good visual appearance. S. Kother et al. [16] applied wavelet techniques for the removal of Gaussian noise is very much effective in de-noising an image with different wavelet bases and also different window sizes, as it is capable of capturing energy in few transforms. Discrete and continuous wavelet transforms shows promising results in image compression, de-noising etc. Firstly, the wavelet transform of the noisy image is computed and the noisy wavelet coefficients are altered by thresholding, finally the inverse transform is computed in obtaining de-noised image.

III. PROPOSED MODEL

The proposed biometric verification model for unimodal and multimodal systems is designed on considering the physiological traits such as face, palm, finger knuckle print, handvein. In the training phase, clean data is considered for the biometric verification system, We have considered various feature extraction algorithms to explore and predict the best feature extractors and we have adopted feature extraction techniques like-Appearance based methods such as Principal component analysis, Linear Discriminant Analysis, Locality preserving Projections, Independent Component Analysis; Kernel based methods like Kernel Principal component analysis, Kernel Linear Discriminant Analysis, Kernel Locality preserving Projections, Kernel Independent Component Analysis; Texture methods like Gabor, Local Binary Patterns Variance, Local Phase Quantization. We have considered all pre and post classification/ matching fusion levels in arriving at the verification rate. On the other side, in testing phase the samples are imposed with Gaussian noise, salt and pepper noise and it is subjected to undergo the feature extraction phases and we are trying to figure out how well the system performs better in noisy databases.

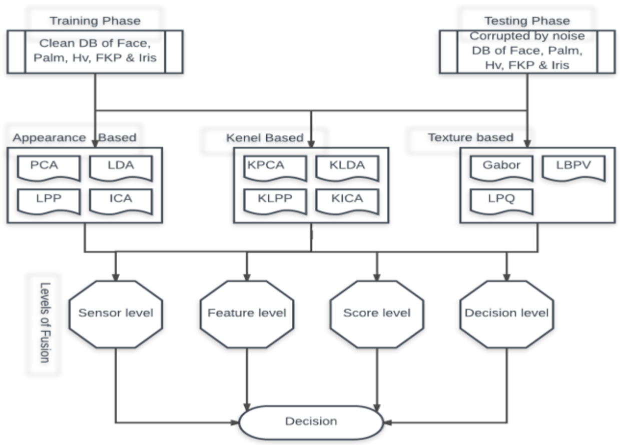

Figure 1. Block diagram of proposed system.

We are analysing the robustness of unimodal and multimodal biometric systems under the Gaussian noise, Salt and pepper noise. We are also trying to get an idea how well the system performs when corrupted by noise? Which feature extraction algorithm extracts discriminating features very well and contributes in the overall accuracy of the system? Which level of fusion is feasible? Which is the optimal combination of traits for fusion?

IV. METHODS AND MATERIALS

In this section, we describe the various methods and techinqeus employed in our work. First we have describe different levels of fusion than various feature extraction algorithms used.

A. *Sensor level fusion*

Wavelet based image fusion : Merging the images obtained from different sensors in obtaining a fused image by wavelet based approach that manages images of different resolutions, that contains rich information[18]. The images to be fused properly aligned by pixel-by-pixel basis and decomposed with different kinds of coefficients by not losing the original information, wavelet transforms has High-High, Low-High, High-Low, Low-Low bands at different scales. The coefficients having higher absolute values retains salient features. The coefficients obtained from different images are collected together in obtaining new coefficients, the most simple way of merging coefficients is to take average of coefficients. The new image is constructed by performing reverse wavelet transformation.

B. *Feature level fusion*

Min-Max: The features extracted from various feature extraction algorithms should be normalized if the features are heterogeneous. This technique maps the scores extracted to the range of $[0,1]$, $N_s = \frac{Fe_i - min(Fe)}{max(Fe) - min(Fe)}$. Fe_i is the feature vector, $max(Fe)$, $min(Fe)$ are the end point scores of the feature vector. Z-score normalization: It employes arithmetic mean and standard deviation of the original input data and calculates the scores by $Z' = \frac{I - mean(Z)}{STD(Z)}$ $mean(Z)$ and $STD(Z)$ denotes the mean and standard deviation of input data Z.

The MAD normalization does not guarantee the common numerical range and is reckless to outliers. The normalization is given as, $N_s = \frac{Fe_i - median(Fe)}{|Fe - median|}$ MAD is not a Gaussian, so it is a poor estimator compared to mean and standard deviation estimators, so it does not retain the common numerical range.

Tanh: The tangent hyperbolic normalization technique, portrays the raw scores to the (0,1) range, $N_s = 0.5\{tanh(0.01 \frac{Fe - mean(Fe)}{STD(Fe)}) + 1\}$ where mean and standard deviation are computed from the matching scores.

C. *Score level fusion*

Min fusion technique utilizes the minimum score values obtained from individual traits as the multimodal score value and it is given by

$min(score_{final}) = min(score_{Palmprint}, score_{face}, score_{FKP}), score_{Hv}$

Max fusion technique takes the maximum score of the individual traits and reflects it as the multimodal score, which is given by

$max(score_{final}) = max(score_{palmprint}, score_{face}, score_{FKP}, score_{Hv})$

Sum rule is adopted generally when there is ambiguity in the decision from individual classifiers. Sum rule fusion is given by

$sum(score_{final}) = score_{Palmprint} + score_{face} + score_{FKP} + score_{Hv}$

D. Principal Component Analysis (PCA)

PCA is a linear transformation technique used for multivariate analysis[17]. PCA technique selects the most discriminant and dominant features from the original features without losing the actual data composition. PCA transforms the correlated variables into linearly uncorrelated variables by linear projection on original variables[1]. The mean from the feature matrix is computed and subtracted from respective column vectors in obtaining the co-variance matrix. Eigenvalues and the corresponding Eigen vectors are computed, the number of features to be selected by deriving threshold. Now the average matrix $\bar{A}$ of all training samples has to be calculated, then subtracted from the original image A_i and the result is stored in ϕ_i.

$A = \sum_{i=0}^{N} A_i$ In the next step, the covariance matrix C is calculated according to $C = \frac{1}{N}\sum_{i=0}^{N} \phi_i \bar{\phi}_i$. The principal components are computed such that it is less than or equal to the original components which are orthogonal and uncorrelated with the greater variance among all computed components. The higher the Eigen values,the more characteristic features of an image can be obtained. The first component has highest variance compared with the succeeding components.

E. Linear Discriminant Analysis (LDA)

Linear discriminant analysis also called fisher discriminant analysis widely practiced and most preferable appearance based technique compared to PCA, as it retains the class information too[17]. LDA opts to choose subspace features that contributes the ratio between class scatter matrix S_o and within class scatter matrix S_i given by, $S_o = \sum_{k=0}^{c} Z_i(x - x_i)(x_i - x)^T$ $S_i = \sum_{k=0}^{c} \sum_{l=1}^{z_i} (y_j - x_i)(y_j - x)^T$ Where c is the total number of classes, z_i is the number of samples in a class, x_i is the mean for the k^th class samples and x is the whole mean i.e mean of the class means. If S_i is non singular, then the projection ratio must be maximized by, $l(w) = argmax_w \frac{|w^T s_o w|}{|w^T s_i w|}$ The class separation in the direction of $\overleftarrow{w}$, w_k $(k = 1,2,3$ contains the largest eigen values with corresponding Eigen vectors.

F. Locality Preserving Projections (LPP)

LPP perpetuates the neighborhood relation among the data set, $l = \{l_1, l_2, l_3 \ldots\ldots l_n\} \subset R^m$ be the sample input set, LPP learns the sample space in projecting it and mapping I into the subspace $o = W^T$ $I = \{o_1, o_2, o_3 \ldots\ldots o_n\} \subset R^d$ in preserving the structure while transforming. Optimal projection W can be computed by minimizing the weighted summation distance between the adjacency points given by, $\sum_{i,j} (o_i - o_j)^2 S_{ij}$ where S_{ij} is weight of i and j^{th} entry in the adjacency matrix, which measures the closeness of the points l_i, l_j in the original data space.

The objective function is given by, $\sum_{i,j} (o_i - o_j)^2 S_{ij} = \sum_{i,j} \sum_{i,j \in c} (o_i - o_j)^2 H_{ij}^c H_{ij}^c$ is the entry in the adjacency matrix of the samples belonging to subject c. Heat kernel is adopted in employing this technique and is given by, if i and j are connected then, $W_{i,j} = e^{\frac{||x_i - x_j||^2}{t}}$ Finally the objective function in LPP reduces to, $2(W^T(D - S)i^T w) = 2W^T iLi^T w$ where $L = D - S$ s the exact graph laplacian.

G. Independent Component Analysis(ICA)

Let $S = [s_1, S_2, s_3, \ldots\ldots s_m]^T$ be the independent source vectors and $O = [o_1, o_2, o_3, \ldots\ldots o_m]^T$ be the observed vector of S, given by =AS , where A is the mixing matrix. The approximated equation in finding the unmixing matrix w is given by $Y \cong WO$ ome of the mandatory prerequisites in finding ICA are- the source signals must be independent, mixing matrix O should be a square matrix, the model should be noise free and the data should have zero mean, Gaussian distribution should be avoided for all kind of source data[17]. Preprocessing is done performing PCA, then then the mixing matrix O is centered and whitening is followed passing O through whitening matrix $W_z = 2 * (CV(o))^{-1/2}$ which removes second order derivatives of the co-variance matrix O. PCA is applied to the components identified by ICA, the most dominant eigenvectors P_m are chosen and the independent vectors are given by, $= WP_m$.

H. Kernel principal component analysis(KPCA)

KPCA is a non-linear dimensionality maps the original input vectors x_i into a high-dimensional feature space $\Phi(x_i)$ and then performs PCA in the feature space whose dimensions are higher than the training samples. $\Phi: x \to \Phi(x)$. The mapped observations having mean centered is an assumption given by, $\sum_{i=1}^{M} \Phi(x_i)$ The covariance matrix in feature space is given by, $\Sigma = \frac{1}{M}\sum_{i=1}^{M} \Phi(x_i)\Phi(x_i)^T$. Solving $\lambda\mu = \mu$ eigenvectors and eigenvalues are achieved, assuming λ is eigenvector and μ is eigenvalue. On transforming the kernel matrix K is obtained by $\delta_i \alpha_i = K\alpha_i$, $i = 1,2, \ldots M$ δ_i is the eigen value and α_i is the corresponding eigen vector of K. The principal components are obtained by $Y_i = \sum_{i=1}^{M} \frac{\alpha_i}{\sqrt{\delta_i}} K(x_i, x)$.

I. Kernel discriminant analysis(KDA)

Let $x_1, x_2, \ldots x_m \in R^l$ be the classes, F be the feature space with nonlinear mapping $\Phi: R^l \to F$ The inner product in feature space may be represented as $(\Phi(x_i), \Phi(x_j)) = d(x_i, x_j)$. The between class scatter matrix is given by, $S_b^{\Phi} = \sum_{d=1}^{c} m_d(\mu_{\Phi}^d - \mu_{\Phi})(\mu_{\Phi}^d - \mu_{\Phi})^T$. Within class scatter matrix is given by, $S_w^{\Phi} = \sum_{d=1}^{c} \sum_{i=1}^{m_d} (\Phi(x_i^d - \mu_{\Phi}^d)\Phi(x_i^d - \mu_{\Phi}^d)^T$ Total scatter matrices is given by,

$$S_t^{\Phi} = S_b^{\Phi} + S_w^{\Phi} = \sum_{i=1}^{m} (\Phi(x_i - \mu_{\Phi})\Phi(x_i - \mu_{\Phi})^T$$

Optimal projection in the feature space is given by,

$V_{optimal} = arg_v max \frac{v^T S_b^{\Phi} v}{v^T S_w^{\Phi} v}$ Each eigen vector v can be represented by, $v_{optimal} = \sum_{i=1}^{m} \alpha_i \Phi(x_i)$

$U_{optimal} = arg_u max \frac{U^T KWKU}{U^T KKU}$ K is the kernel matrix and W is the number of samples in the class. Once the α_i the coefficients are found, the projection in the feature space could be easily analyzed with the eigen vectors v. $(v, \Phi_i) = \sum_{i=1}^{m} \alpha_i(\Phi(x_i), \Phi(x))$.

J. Kernel locality preserving projections(KLPP)

To generalize LPP to nonlinear manifold learning, $KLPP$ is depicted here. Suppose that the Euclidean space $R^d h$ is mapped to a high-dimensional Hilbert space through a nonlinear mapping function is Hilbert space H through a nonlinear mapping function $\Phi: R^d h \to H$, Define the following kernel function: $K(O_i, O_j) =< \Phi(O_i), \Phi(O_j) >= \Phi_T(O_j)\Phi(O_i)$ Objective function is minimized by having minimum Eigen values, the two matrices KLK and KDK are both symmetric and positive semi definite $KLK\alpha = \lambda KDK\alpha$ Let the column vectors $\alpha_0, \alpha_1, \ldots. \alpha_{dL}$ be the solutions ordered according to their eigenvalues, $0 = \lambda_0 \leq \lambda_1 \leq \lambda_2 \ldots \leq \lambda_{dL}$ The maps can be obtained by $y = k\alpha$.

K. Kernel Independent component analysis(KICA)

The Kernel ICA method is based on novel kernel-based measures of dependence. The input space is projected with the kernel trick into a high dimensional feature space called the reproducing kernel Hilbert space (RKHS) in generalizing the eigenvector problem.F-correlation between the random variables s_1 and s_2 and hence their F-correlation is 0.

$$\rho_F = MAX_{f_1, F_2 \in F} \frac{correlation(f_1(s_1), f_2(s_2))}{(Var(f_1(s_1))^{1/2}(Var(f_2(s_2))^{1/2}}$$

Canonical correlation analysis is the extended algorithm of PCA, which leads to generalized Eigen vector problem in in reconstructing kernel Hilbert space in forming block matrices, $K_k \alpha = \lambda D_k \alpha$.

L. Local Binary Patterns Variance (LBPV)

LBP is a powerful texture descriptor introduced by Ojala et al. [8] that characterizes the spatial structure in local neighborhood. The basic LBP operator thresholds the image pixels by $3 * 3$ neighborhood of each pixel with center value a pattern is computed by, $LBP_{A,B} = \sum_{A=0}^{A-1} d(g_n - g_c)2^A$

$$d(x) = \begin{cases} 1, & \text{if} x \geq 1 \\ 0, & \text{otherwise} \end{cases}$$

g_c is the gray value of center pixel, g_n is the pixel value of its neighborhood, a is number of neighborhood pixels, b is the radius of neighborhood. Suppose the coordinates of g_c are $(0,0)$, then the coordinates of g_n are given by $(-Rsin2\pi A/A), -Rcos(2/A))$. $LBP_{A,B}/VAR_{A,B}$ operator provides complimentary information of local spatial pattern and contrast information. The threshold is calculated to partition the distribution into N bins in seeking high quantization resolution. $LBPV$ is given by,

$$LBPV_{AB} = \sum_{i-1}^{N} \sum_{j-1}^{M} W(LBPV_{AB}(i,j), k), k \in [0, k]$$

$$W(LBPV_{AB}(i,j), k) = \begin{cases} VAR_{AB}(i,j), & \text{if} LBP_{AB}(i,j) = k \\ 0, & \text{otherwise} \end{cases}$$

M. Gabor filter

Gabor is one of the texture descriptor introduced by D. Gabor in 1946[9]. Gabor filter is basically a non-orthogonal wavelet and it is a Gaussian function modulated by complex sinusoidal, $g(x,y) = \frac{1}{2\pi\sigma_x\sigma_y} \exp\left(-\frac{1}{2}\left(\frac{x^2}{\sigma_x^2} + \frac{y^2}{\sigma_y^2}\right) + 2\pi jWx\right)$

σ_x σ_y denotes the standard deviation of the Gaussian function w.r.t x and y directions. W is the frequency of the sinusoidal plane. Let $g(x,y)$ through generating function, $g_{mn}(x,y) = a^{-m} g(x,y)$ Where m and n are integers specifying the scale and orientation. Total number of scales and orientations given by, $x = a^{-m}(xcos\theta + ysin\theta$ and $y = ycos\theta - xsin\theta$.

N. Local Phase Quantization(LPQ)

Convolution between image intensity and point spread function in an image constitutes spatial blur. In the frequency domain it is given by, $B = OP$, where B is the discrete fourier transform of blurred image, O is the original image and P is PSF respectively. On dealing with only phase information $B = O + P$, P is always real valued if the blur is centrally symmetric i.e $P \in (0, \pi)$ If the PSF is Gaussian or a sin function, then $P = 0$, causing original image to be blur invariant. LPQ extracts the information using a short-term Fourier transform calculated over a rectangular window W at each pixel position y of image $f(y)$ given by,

$$F^s(k,u) = \sum I \in Z^2 F(I) * w(K-1) * e^{-j2\pi(k-I)^T} u$$

where k is the position and u is the 2D-frequency. The local Fourier coefficients are computed at four frequency points $u_1 = [a, 0]^T$, $u_2 = [0, a]^T$, $u_3 = [a, a]^T$, $u_1 = [a, -a]^T$ satisfying $p(u_i > 0)$. The coefficients are quantized using, $Q(F(k,u) = (Re\{F(k,u)\}) + (Im\{F(k,u)\})$.

V. EXPERIMENTAL ANALYSIS

In this section, we have verified the robustness of various biometric modalities and feature extraction algorithms at different levels of fusion, under two distinct noise conditions namely Gaussian and Salt & Pepper.

A lot of researchers in the literature emphasize these noise models (Gaussian and Salt & Pepper) as practical real time issues. Since we are applying additive noise, we considered only image type biometric modalities, another reason for this is sensor level fusion cannot be performed other than image modalities. Hence we considered publicly free available biometric databases and created our own virtual multimodal databases, the employed databases are as follows 1) AR Face: face recognition is widely used from past decades and finds enormous applications in security surveillance and border security needs 2) PolyU Palmprint and Finger knuckle print(FKP) : Palmprint is relatively a larger region hand based modality comprising lot of minutiae features and ridges on it and FKP is an emerging trait that consists of creases and skin folds containing rich texture information which has high user acceptance 3) Cluj Handvein database : The vein pattern in the handvein(HV) modality develops before the birth and remains stable, and skin protects it from external distortion. We considered 100 users in each modality; for each user three views were used for training and two for testing.

1) *Modeling Spatial Noise*

In this subsection, spatial noise has been added to different biometric trait of image type, which is modelled by the statistical behaviour of the gray level values. This can be viewed as random variables, characterized by the Probability Distribution Functions (PDF)[7]. There are different Spatial Noise generating techniques through continuous distributions in literature, namely Gaussian noise, Weibull noise, Exponential noise, Salt and Pepper noise and Beta Noise with varying in its PDFs. We have used only two types of real time noise in our experiments such as Gaussian and Salt and pepper noise. The following are the PDFs that we use in order to model the spatial noise[6].

Gaussian noise: also called as amplifier noise which is used as additive white Gaussian noise[5]. In a Gaussian noisy image, each pixel deteriorated has the pixel value of both true and random values, as the noise is statistically independent (uncorrelated).In a digital image, Gaussian noise usually occurs during data acquisition (poor sensors). $p(s) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(g-\mu)}{2\sigma^2}}$ where g is gray level, μ is the mean and σ is the standard deviation. Where z is the gray value, μ is the mean of s, and σ is its standard deviation. The control parameters μ and σ define $\mu = 0.2$ and $\sigma = 0.1$ and noise generated for different modalities is as shown in Figure 2.

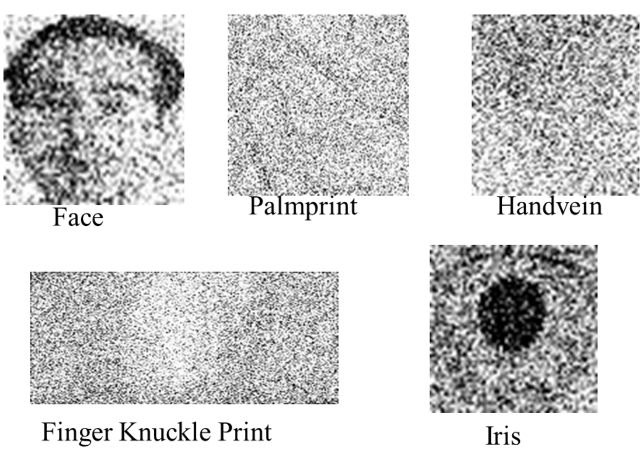

Figure 2. Different biometric traits corrupted by Gaussian noise.

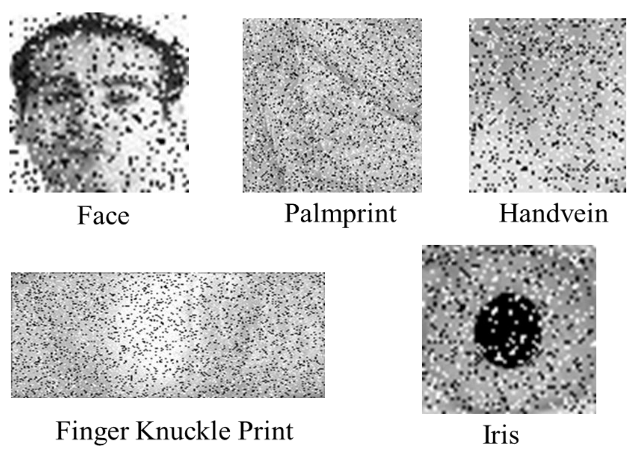

Figure 3. Different biometric traits corrupted by Salt and pepper noise

We have investigated and compared the performance of data on employed modalities for both clean and noise corrupted. Initially, we have analyzed the robustness of unimodal systems with distinct modalities and further we have analysed the robustness of a multimodal system with different combinations of two, three and four modalities at different levels of fusion. The modality, feature extraction algorithm, or levels of fusion are said to be more robust if and only if the rate of percentage of decrease in GAR is less in noise corrupted data as compared to clean data.

Salt and pepper noise: It is a randomly occurring black and white pixels or both in a certain amount of pixels in a image which is usually generated during data transmission, malfunctioning of camera sensor cells. Salt and pepper noise can have only 2 possible values s, p. The intensity of pepper noise is close to 0 and salt noise is close to $saltandpepper = \frac{Pforg = p("pepper")}{Sforg = s("salt")}$ Given the probability x (with 0 x 1) salt-and-pepper noise cab be induced by choosing $x/2$ randomly selected pixels to black, and another fraction of $x/2$ randomly chosen pixels to white. We have used the standard Matlab command *imnoise* to create the salt and pepper effect for a given image, some of noise corrupted images shown in Figure 3.

2) Performance Evaluation

In this subsection, we investigate the robustness of modalities, feature extraction algorithms and fusion strategies. The feature extraction algorithms which we have used are a) Appearance based b) Kernel based and c) Texture based algorithms. In Appearance based, we have used Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), Locality Preserving Projections (LPP) and Independent Component Analysis1 (ICA1). In Kernel based, we have used Kernel Principal Component Analysis (KPCA), Kernel Discriminant Analysis (KDA), Kernel Locality Preserving Projections (KLPP) and Kernel Independent Component Analysis (KICA). In Texture based feature extraction algorithms, we have used Local Binary Patterns Variance (LBPV), Local Phase Quantization (LPQ) and Gabor.

The different fusion schemes which we have applied are sensor level, feature level, score level and decision levels. The corresponding fusion rule used at sensor level is wavelet based image fusion. At feature level different feature normalization rules have been used that are min-max, z-score, Tanh and median. At score level min, max and sum rule have been used whereas at Decision level AND OR rules were applied. The performance is measured in terms of GAR% at 0.1 FAR% for clean and noise corrupted images and the rate of percentage decrease in GAR% of clean and noisy data obtained by various feature extraction algorithms was evaluated as well. The formula used to calculate rate of change of GAR% is as follows:

$$Rate\ of\ Decrease = \frac{Clean\ data - Noisy\ data}{Clean\ data} X100.$$

We have added Gaussian noise of mean 0.2 and variance 0.1 to the selected modalities. We have measured the performance of noise corrupted modality and compared it with its corresponding clean modality. Table 1 shows the performance robustness of all the modalities with respect to different feature extraction algorithms under Gaussian and Salt \& Pepper noises respectively. We can observe that for face modality, Independent Component Analysis, Kernel Independent Component Analysis and Local Phase Quantization are performing well with 81%, 81% and 80.5% of GAR respectively. ICA1 and KICA are consistent in performance with clean data as well as noisy data. ICA and KICA under both kinds of mentioned noises (Gaussian, Salt & Pepper) has achieved lower rate of decrease of GAR (3.7%, 2.47%) and (4.32%, 3.7%) respectively which can be visualized in Figure 4. Whereas, LPQ performance has reduced abruptly with the high rate of decrease to (69.56%, 64.59%) when performing with both kinds of noisy data. Hence, the LPQ feature extraction algorithm is not robust to the noise as it performs well only to clean data, one cannot rely on this feature extraction algorithm. So, for the biometric verification system based on face modality ICA and KICA algorithms are most suitable feature extractors.

On performance of the unimodal plamprint biometric verification system, the texture based technique LPQ has obtained high GAR of 87.5% for clean data but while performing with noisy data, it is not consistent and has obtained higher rate of decrease in GAR (48%, 46.28%). Whereas, KDA seems to be consistent on both clean and noisy data, as its GAR is 67.5% for clean data and low rate of decrease of (16.29%, 13.33%) for the mentioned noises. Table 1 also shows the GAR tabulated results from various feature extraction algorithms in implementing a unimodal biometric verification system for Finger Knuckle Print modality under clean and noisy data (Gaussian noise, Salt & Pepper noise). On observing the obtained results, one can infer that Texture feature algorithms such as LPQ and Gabor under clean data are performing best with 88.5% and 86% GAR resepectively.

However, they fail to maintain the stability under noisy data conditions, as the performance reduces to half. The subspace methods opted for our experimentation such as LDA, ICA are also performing better with considerable verification rate. ICA seems to be stable while performing on both clean and noisy condition data. KLPP is the worst performer for both kinds of data.

The efficiency regarding robustness of handvein modality is analysed with different feature extraction algorithms under the previously mentioned noises. LPQ method shows least decrease in GAR with 22.37% and 23.68% for the respective noises, making it the most robust feature extraction algorithm among selected methods. Gabor technique performs well for clean data with 54% of GAR, however, while dealing with noisy data the performance deteriorates almost half (with 25.5% decrease in Gaussian and 27% in Salt & Pepper). PCA method performs well for clean handvein whereas for noise corrupted Gaussian and Salt & Pepper it performs poorly with high percentage of decrease in GAR as (36.76%, 51.04%) respectively. Hence, the PCA feature extraction algorithm can be used for clean data only but not for noise corrupted data.

3) Robustness Analysis of Multimodal Biometrics

Multimodal System Corrupted by Gaussian Noise, Salt and Pepper Noise: In this subsection, the robustness of multimodal systems has been analysed for Gaussian noise and Salt & Pepper noise using different combinations of multimodal system with the best fusion modalities. The robustness of feature extraction, different levels of fusion and their rules and normalization techniques are also evaluated. The performance is measured in terms of GAR% at 0.1

FAR% for clean and corrupted by Gaussian and Salt & Pepper noise images. The rate of percentage decrease in GAR% of clean and noisy data is tabulated.

Robustness of bimodal system is measured on KICA features of Face and LPQ features of Palmprint at different levels of fusion. In Table 2 we can observe that, fusion of two modalities give better results compared to its unimodal case. The two stages of fusion done here are; 1)fusion of KICA and LPQ features for clean data and 2) fusion of KICA and LPQ features of corrupted data by the mentioned noises imposed on Face and Palmprint modalities. The evaluation infers that, fusion of modalities corrupted by noise give different results as compared to fusion of clean modalities. Feature level fusion with Tanh normalization rule performs well for noisy data and is proved to be consistent with both kinds of data.

It seems to be more robust among other rules with lower rate of decrease in GAR (17.55% in Gaussian and 16.49% in Salt & Pepper), which can be viewed in Figure 5. At the same time, feature level fusion with Min-Max normalization rule performs worst with rate of decrease in GAR as (78.19%, 77.65%). In clean data, the score level fusion on its Sum rule performs well among the other level of fusion. For the same combination modalities corrupted by both kinds of noise, score level fusion on sum rule performs poorly.

In Decision level fusion with OR rule the system is showing stable performance under clean and noisy data. Hence, the fusion of similar modalities on same feature extraction algorithms behave differently on noisy and clean data. It shows that, for robustness analysis not only modalities and feature extraction methods play a vital role but also the appropriate levels of fusion with its corresponding rules are significant in the multimodal approach.

Robustness on fusion of three modalities is measured namely; KICA1 features of face, LPQ features of Palmprint and LPQ features of FKP are fused at different levels of fusion. Table 2 represents that combination of three modalities perform better than the combination of two modalities on noisy as well as clean data. Wavelet based sensor level fusion under performs on both clean and noisy data. In feature level fusion, all the selected rules i.e. Z-score, Median, Min-Max, Tanh, perform well in case of clean data in with GAR% of 96.5%, 96.5%, 93.5%, 93.55% respectively.

However, Tanh is stable and out-performing in case of of clean as well as noisy data. At the score level fusion, Sum rule has got the highest verification rate of 99.5% on clean data out of all the considered rules but it under performs on noisy data. In decision level fusion, OR rule seems to be most stable on both kinds of data.

Performance of fusion of four modalities of clean and corrupted by noise data is also measured. KICA1 features of face, LPQ features of Palmprint, LPQ features of FKP and Gabor features of Handvein are fused at different levels fusion. The accuracy in sensor level fusion has degraded from 39% to 20% of GAR when handvein modality was fused with other three traits, making it unreliable. In feature level fusion the performance obtained from employed rules have increased GAR% rate on fusion of another modality, where Tanh rule is performing outstanding on both clean and noisy data. In score level fusion, though the Sum rule is yielding 100% verification rate, it is not feasible in handling noisy data. Or rule in decision level fusion is performing quiet efficient even for noisy data.

4) Some Key Points based on the Experimental results

With respect to modality and data corrupted by Gaussian and Salt & Pepper noises, the best and worst performances of unimodal biometric verification system are given as follows:

Modality	Gaussian		Salt and Pepper	
	Best	**Worst**	**Best**	**Worst**
Face	ICA	LBPV	ICA1	LBPV
Palmprint	KDA	LBPV	KDA	LBPV
Handvein	LPQ	KLLP	LPQ	LBPV
FKP	LPQ	LBPV	ICA1	LBPV

With respect to fusion strategies on data corrupted by noise the best and worst performances are given below:

Level of fusion	**Best**	**Worst**
Score level	Sum	Min
Feature level	Tanh	Min-Max
Decision level	OR	AND

In terms of Rate of decrease in performance best and worst levels of fusion and rules for different multiodal systems corrupted with Gaussian noise are as under:

Multimodal	**Best**	**Worst**
Face+Pp	Feature(Tanh)	Feature(Min-max)
Face+Pp+FKP	Decision(OR)	Feature(Min-max)
Face+Pp+FKP+Hv	Feature(Tanh)	Feature(Min-max)

In terms of Rate of decrease in performance best and worst levels of fusion and rules for different multiodal systems corrupted by Salt & Pepper noise are mentioned below:

Multimodal	**Best**	**Worst**
Face+Pp	Feature(Tanh)	Feature(Min-max)
Face+Pp+FKP	Decision(OR)	Feature(Min-max)
Face+Pp+FKP+Hv	Decision(OR)	Feature(Min-max)

VI. CONCLUSION AND DISCUSSION

The design of a multimodal system is governed by several factors, including choices of modality, feature extraction algorithms, the type of modalities to be combined, and the fusion strategy to be employed. Generally, it is difficult to predict the ideal biometric trait relevant for a particular application. There is tendency towards saturation with every additional modality. A careful choice of minimum number of modalities can yield desired level of performance, even it is hard to measure the choice of feature extraction algorithm which provides complementary/supplementary strengths to the system, the appropriate fusion methodology based on recognition performance alone. Finally, the development of a robust system which performs significantly well even when the data is corrupted by noise is necessary. Some of the factors such as cost of system deployment, throughput time, user convenience, scalability, etc. also play a large role in selecting appropriate modality, feature extraction algorithms and fusion strategies. Trade-off arises between information content and ease of fusion. By only increasing the number of modalities in a multimodal system, will not yield the desired recognition rate. Rather, appropriate selection of lesser number of modalities and their best combination will produce desired level of performance. From our obtained results we can conclude that,

1) Finger knuckle print modality based unimodal biometric system with the LPQ feature extraction technique is yielding 88.5% of highest GAR, when compared to other considered modalities.

2) Sensor level fusion with wavelet based rule is desirable up to fusion of two modalities only, and gets unstable for any higher number of fusion of modalities.

3) The order of robust fusion levels and it corresponding rules with respective to performance on noisy data are, i)Decision level: OR rule ii)Feature level: Tanh normalization and iii)Score level: Max rule

4) Three robust fusion level and rules with respect to of rate of decrease are, i)Feature level: Tanh normalization ii)Decision level: OR rule and iii)Score level: Max rule

Generally in multimodal systems, it is difficult to predict the optimal sources of biometric information relevant for a particular application and the appropriate fusion methodology based on performance alone. Most of biometric systems perform well on clean data; however, robust feature extraction algorithms/ fusion strategies are essential to efficiently handling various kinds of noises.

TABLE 1: Robustness comparison of face, palmprint, fkp and hv unimodal systems of GAR % at 0.1% FAR under clean and corrupted by gaussian noise, salt and pepper noise

Feature Extraction	Face			Palmprint(Pp)			Finger Knuckleprint(FKP)			Handvein(Hv)		
	Clean	GN	SPN	Clean	GN	SPN	Clean	GN	SPN	Clean	GN	SPN
PCA	40.5	36	36.5	52	37.5	39	69.5	42	41	48	21.5	23.5
LDA	69.5	58.5	44	58.5	40	42	78	44.5	46	16	10	11
LPP	46	26.5	26	50	32.5	36.5	61.5	36.5	39.5	6	3.5	4
ICA1	81	78	79	65.5	50	54	77.5	50	52.5	46	25.5	26.5
KPCA	63	40.5	42	64	36	39	69	38.5	41.5	35.5	22	25.5
KDA	64.5	41.5	43.5	67.5	56.5	58.5	67	35	38	16	11	12
KLPP	57	26	28	54	28	26	58.2	27	30.5	3.5	2	2.5
KICA1	81	77.5	78	79	56	58	59.5	32	33.5	19.5	9	11
LBPV	9	7.5	8	42	22.5	25	19.5	12	13.5	17	11.5	12.5
Gabor	65	35.5	37.5	55.5	30	32	86	43	45	54	25.5	27
LPQ	80.5	24.5	28.5	87.5	45.5	47	88.5	46.5	48.5	38	29.5	29

Table 2: robustness comparison of multimodal system gar% at 0.1%far on fusion of up-to four modalities face (kica1), palmprint(lpq), finger knuckleprint(lpq) and handvein(gabor) for both clean and corrupted by gaussian noise, salt and pepper noise

Fusion	Rules	Face+Pp			Face+Pp+FKP			Face+Pp+FKP+Hv		
		Clean	Gaussian Noise	Salt and Pepper	Clean	Gaussian Noise	Salt and Pepper	Clean	Gaussian Noise	Salt and Pepper
Sensor Level	*Wavelet based*	35	20	22	39	18	19	20	13	11
Feature Level	*Min-Max*	94	20.5	21	93.5	18	21	96.5	40	41.5
	Z-score	93.5	39	36	96.5	38.5	41.5	97	46	51.5
	Median	93.5	39	41	96.5	41	42	97	52.4	56.5
	Tanh	94	77.5	78.5	93.5	72.5	74	96.5	76.5	77.5
Score Level	*Min*	85	44	41	91.5	48.5	50.5	92	48.5	46.5
	Max	93.8	68.5	71.5	95	62	63	94.5	62	60
	Sum	95	50	52.5	99.5	50	48	100	65	62
Decision Level	*OR*	94	73	75.5	96	74.5	76.5	95	74.5	76.5
	AND	85	43.5	44.5	92	46	48.5	91	61	63.5

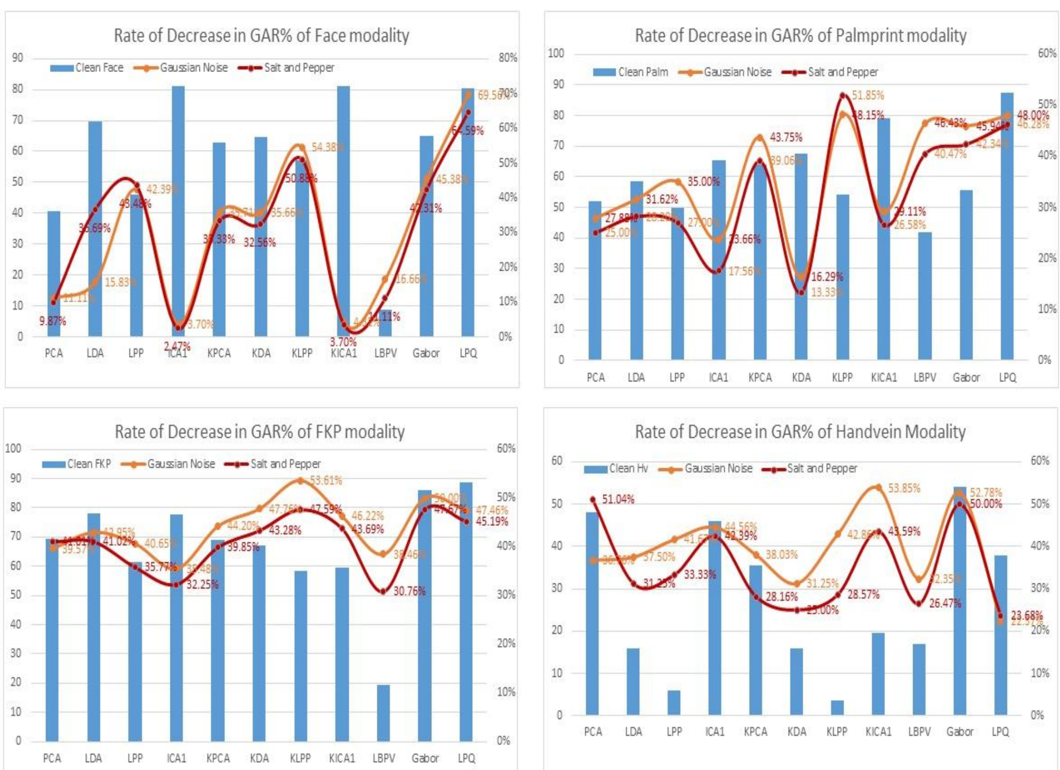

Figure 4. Different BAR chart to analyze %Rate of Decrease for different feature extraction algorithms on Different unimodal biometric systems corrupted noise.

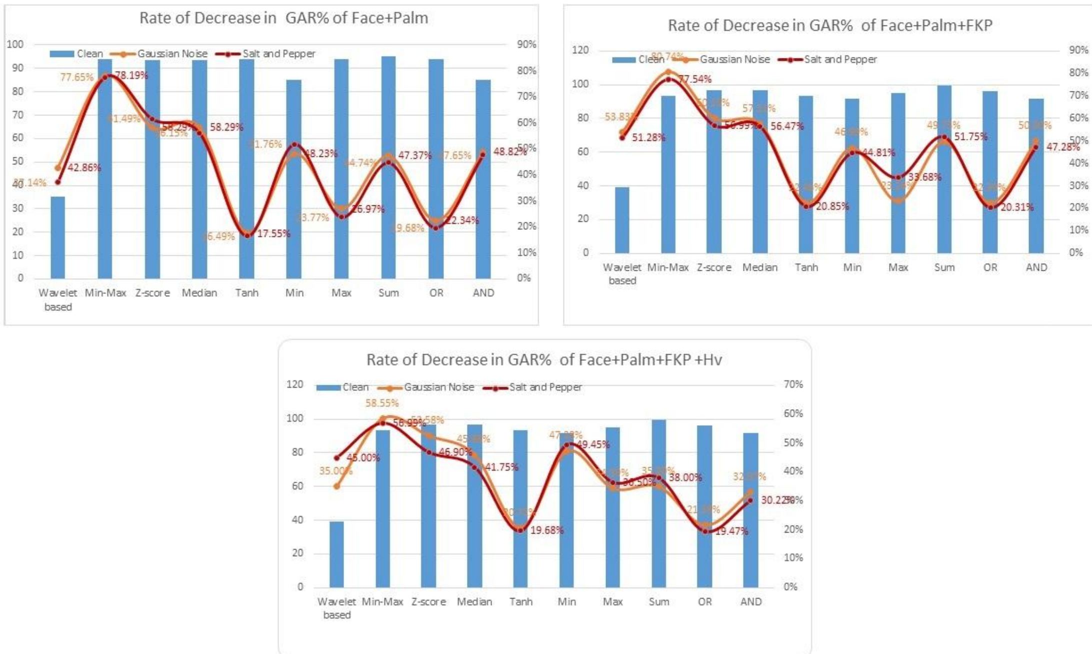

Figure 5. BAR chart to analyze %Rate of Decrease for different fusion strategies on Different multimodal biometric system corrupted by noise

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