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Bimodal Biometric Verification Mechanism using Fingerprint and Face Images(BBVMFF)

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***Abstract*— An increased demand of biometric authentication coupled with automation of systems is observed in the recent times. Generally biometric recognition systems currently used consider only a single biometric characteristic for verification or authentication. Researchers have proved the inefficiencies in unimodal biometric systems and propagated the adoption of multimodal biometric systems for verification. This paper introduces Bi-modal Biometric Verification Mechanism using Fingerprint and Face (BBVMFF). The BBVMFF considers the frontal face and fingerprint biometric characteristics of users for verification. The BBVMFF Considers both the Gabor phase and magnitude features as biometric trait definitions and simple lightweight feature level fusion algorithm. The fusion algorithm proposed enables the applicability of the proposed BBVMFF in unimodal and Bi-modal modes proved by the experimental results presented.**

I. INTRODUCTION

Biometric based verification systems have been proved beneficial for securing resources. Biometric verification can be achieved through a user's behavioral and/or physiological characteristics [1]. Predominantly the user's physiological characteristics like iris frontal face, palm print finger print, etc. are used in verification systems [2]. Biometric verification is adopted for varied commercial applications ranging from access control, attendance management [3] to medical analysis [4]. Generally in biometric verification systems, the biometric data acquired from the sensors is processed to identify the features. The features extracted are used to define the varied users of the biometric systems. The features extracted from the biometric data are analyzed using machine learning techniques. Thus, it can be stated that to establish robust verification systems biometric data acquisition need to be accurate and error free.

The biometric data acquisition mechanisms suffer from a number of drawbacks [1] [5] discussed in the further section of this paper. To overcome these drawbacks researchers have proposed the use of multimodal biometrics [1] [5] [6] [7]. To incorporate multiple biometric characteristics into the verification systems a fusion algorithm is necessary. The fusion algorithms can be broadly classified [8] as sensor based [9], feature based[10], decision level based [11] or score based [6]. In sensor based fusion techniques the biometric data acquired from varied sensors is combined such that the resultant is accurate and more informative. In feature based fusion techniques the feature vectors extracted from the individual biometrics are combined to produce a comprehensive multimodal feature vector.

According to A. Ross et.al., [5] the feature level fusion techniques are highly efficient and are computationally light when compared to the other fusion techniques. The major drawback of the feature level fusion technique is that the fused data is of large dimensions and addition reduction techniques are required. The decision level fusion technique is primarily democratic in nature where in each biometric characteristic is processed individually i.e. feature extraction, matching and verification. The resultant decision is derived based on the decision majority observed. In matching score based fusion technique. The individual biometric features extracted are compared with the test data corresponding to the equivalent biometric characteristic. A cumulative equivalent score is derived using non- linear or linear equations.

Organization: The remaining manuscript presented here is organized as follows: In Section II a brief of the related work studied is presented. The background is presented in Section III. The proposed BBVMFF is discussed in Section IV. The results and performance comparisons is discussed in the penultimate section of the paper. The conclusions and future work are presented in the last Section.

II. RELATED WORK

Over the past few years, multimodal biometric verification systems is an active research area. Some of the state of art verification systems are as follows:

Teddy ko et al., [12] have overviewed different multi model fusion systems using iris, fingerprint and face identification, the fusion level and different integration strategies are used to fuse data and to improve the overall system efficiency. And also they overview on improving the essence of these biometric samples or data. The analytical result shows that the score level fusion achieve good flexibility and improve accuracy. They conducted this experiment on NIST dataset. In order to get better result or accuracy one has to use larger dataset.

Ravi s et al., [13] have analysed various biometric system and point it out the pros and cons of different biometric model. Due to the drawback of unimodal biometric many multi modal biometric system was developed. Here they point out the drawback of different multimodal and showed the importance of having strong modalities by using fingerprint, face recognition and enhanced iris features.

Shekhar S et al., [14] have developed a multimodal sparse depiction approach that illustrates the test information using a inadequate linear combination of training information. In their research they have taken into consideration of the correlations as well as the coupling of varied information in different models under use. In order to achieve non-linearity they employed Kernels and further they enhanced their system using an alternative directional approach.

Zhenhua Chai et al., [15] employed Gabor ordinal measures (GOM) scheme for face feature extraction and they enhanced the system using Gabor features with the effectiveness of ordinal estimations as a potential solution that could ensure both inter-person resemblance and intra-person deviations for face image data. In their system they employed varied categories of ordinal estimations derived from its intensity, phase, magnitude and real and imaginary components of Gabor filter. Ultimately, they employed a two phase cascade learning scheme and a greedy block selection approach that could be employed for training certain classifier for face data. In their research they emphasized on face recognition accuracy.

Besbes et al., [16] have developed a multimodal biometric system using features of face and fingerprint images**.** Here they have used a combination approach by fusing Face and finger print which is based on unimodal verdict using an "AND" operator. The encoding scheme of biometric data is based on mathematical representation of Face features. The problem with this model is that there is no experimental evidence or analysis on recognition performance.

Telgad R L et al.,[17] have proposed the combination approach of Bimodal Biometric system using face and fingerprint images to fusion of score level . The features extracted in the system are used for matching using Euclidian distance matcher for face and fingerprint images. Fingerprint recognition is obtained using minutiae matching and Gober filter method. And also face features are extracted using PCA (Principle Component Analysis) for measurement shrinking. Then the matched scores are formalised and fusion of score level is developed in this system.

Deshmukh, A et al.,[18] have proposed a mulitmodal biometric authentication system on Feature level fusion of face and fingerprint images using Gabor filter bank. They have used Linear Discriminant Analysis and Principal Component Analysis framework in their work to avoid imprecation of dimensionality in feature set and introduced a good discriminating ability. Experimental results of feature level fusion has been showcased against unimodal biometric recognition. The recognition accuracy of 99.25% have been achieved in their work.

III. BACKGROUND WORK

To improve the performance in BBVMF , the adoption of Gabor phase and magnitude features for definitions of multimodal biometric characteristics is considered and a better classification algorithm in the form of the weighted *k* nearest neighbour is adopted. The experimental results discussed in the later sections of the paper prove the multimodal scenarios.

IV. Bimodal Biometric Verification Mechanism using Fingerprint and Face Images (BBVMFF)

4.1. *Problem Formulation*

Let the set $\mathcal{T} = \{t_1, \cdots, t_{\mathcal{P}}\}$ represent the training set of $\mathcal{P}$ registered users, where $t_{\mathcal{P}}$ represents the Bi-modal biometric definition of the p^{th} user. Let the unknown user set be $\mathcal{U} - \{u_1, \dots, u_y\}$ where u_y is the Bi-modal definition of the y^{th} unknown user. Let $Sc(x, y)$ represent the similarity computation function between the Bi-modal definitions x and y . The verification problem arises to identify, if the unknown user $y \in \mathcal{P}$.

Let $V(i, d)$ represent the verification function, where i is the user identification variable and d is the Bi-modal definition. Using the function V the verification problem can be defined as

$$V(y, u_y) = \begin{cases} \mathcal{P} & if\ Sc(u_y, t_y) \geq \tau \\ \mathcal{I} & if\ Sc(u_y, t_y) < \tau \end{cases} \quad (1)$$

Where $\mathcal{I}$ is the imposter is set or unregistered user set and τ is the accuracy threshold established.

4.2. *System Model*

Let $\mathbb{T}$ represent Bi-modal dataset of $\mathcal{P}$ users defined as

$$\mathbb{B} = \{\mathbb{f}^{\mathcal{P}} \cup \mathbb{p}^{\mathcal{P}}\} \quad (2)$$

Where $\mathbb{f}^{\mathcal{P}}$ represents the frontal face biometric data and $\mathbb{p}^{\mathcal{P}}$ is the fingerprint biometric data.

The BBVMFF model is shown in Fig.1. Pre-processing is applied to the biometric data acquired to identify the ROI . The ROI's identified using image processing techniques are represented as $\mathbb{F}^{\mathcal{P}}$ and $\mathbb{P}^{\mathcal{P}}$. The biometric feature definitions are extracted using the Gabor filters.

The phase features $\mathcal{G}$ and the magnitude features $\mathcal{G}$ are considered to obtain the Gabor definition set $\bar{\mathcal{G}}$. The variable h denotes the fused Gabor definitions of the frontal face and finger print for every user. The resulting fused definition set is represented by $\mathbb{B}^{h\times\mathcal{P}}$. Dimensional reduction is adopted to improve the response time of the BBVMFF resulting in to $\mathbb{B}^{r\times\mathcal{P}}$ where $r \ll h$. The BBVMFF adopts the Weighted KNN classifier to solve the verification problem described earlier.

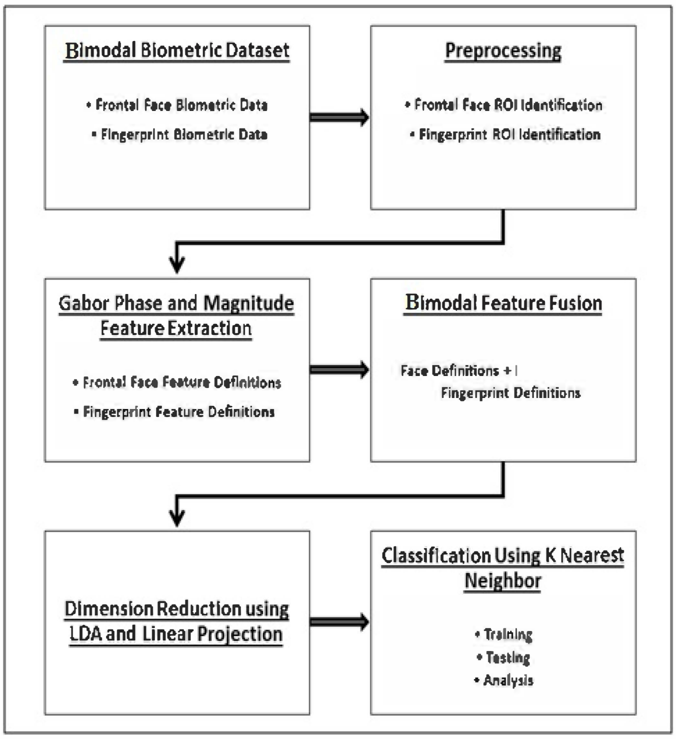

Fig. 1. System Architecture

4.3. *BBVMFF Pre-Processing*

a. *Frontal Face ROI Identification*

Localization, segmentation and face, non-face classification techniques are adopted in the BBVMFF to obtain the frontal face ROI[23][24].

The face regions identified in $\mathbb{f}_n$ are utilized to obtain the face ROI. The face ROI images are then converted to greyscale images utilizing the $_{BBVMFF}^{G.Scale}FP(\mathbb{v}_x)$ function. The greyscale frontal face ROI dataset constructed is defined as

$\mathbb{F} = \{\mathbb{F}_1, \mathbb{F}_2, \mathbb{F}_3 \ldots \mathbb{F}_{\mathcal{P}}\}$	*(3)*

A sample input image for the $\mathcal{P}^{th}$ user i.e. $\mathbb{f}_{\mathcal{P}}$ and the ROI image $\mathbb{F}_{\mathcal{P}}$ is shown in Fig.2.

Frontal face $\mathbb{f}_{\mathcal{P}}$ ***ROI* frontal face $\mathbb{F}_{\mathcal{P}}$**

Fig. 2. Frontal face ROI identification

b. *Fingerprint ROI Identification*

The fingerprint biometric image set $\mathbb{p}$ of $\mathcal{P}$ users can be represented as $\mathbb{p} = \{\mathbb{p}_1, \mathbb{p}_2, \mathbb{p}_3 \ldots \mathbb{p}_{\mathcal{P}}\}$. The ROI of the fingerprints is identified by the compact confined length finger codes. The finger codes are extracted using Gabor filters that capture both local details as well as global details of the fingerprint. The identification of fingerprint and its ROI has been achieved by means of Euclidean distance between the two corresponding finger codes. The detection of fingerprint biometric core is of high significance. The ROI identified is centered around the core point.

To identify the core point is estimated the orientation field. Detecting the core point, the circular region around the core point into certain defined sectors. The intensities of associated pixel were normalized for certain fixed mean and variance. In identification the circular space was filtered with a robust of Gabor filters. The mean absolute deviation within a divided space enumerates the vital ridge structure which was further employed as feature. For identification a feature vector was prepared which collected the local information and sequential enumeration of the tessellation exhibited the static global relationship amongst all local patters. The key step for fingerprint detection is Core Point Detection.

The core point is nothing else but a high curvature space in the fingerprint which is completely dependent on ridge's orientation. On the other hand, to perform precise fingerprint ROI identification locating accurate core point is a significant task.

Let, $\dot{e}$ represents the orientation field of a biometric fingerprint image $\mathbb{p}_{\mathcal{P}}$ and $\dot{d}(l,e)$ is the local ridge orientation at certain (l,e) pixel. In BBVMFF, the local ridge orientation is specified for a pixel block. In this process initially the image is separated into a cluster of non-overlaying block of size $z \times z$ which is followed by estimation of the gradient factors $G(l,e)$ and $H(l,e)$ at individual pixel which is at the center of divided blocks. The local orientation is estimated using the following equations and select the gradient operator as per computational complexity.

$_{BBVMFF}^{LclOrient}PP_a(l,e) = \sum_{m=l-\frac{Z}{2}}^{l+\frac{Z}{2}} \sum_{n=e-\frac{Z}{2}}^{e+\frac{Z}{2}} 2\partial_a(m,n)\,\partial_{b(m,n)}$	**(4)**

Where $\partial_a(m,n), \partial_{b(m,n)}$ represent the gradients computed. From Eq. 9 the orientation field is computed $O'(l,e) = (1/2)tan^{-1}[\phi_b'(l,e)/\phi_a'(l,e)]$. To convert the orientation image into a vector field and to reduce the noise on the fingerprint ridges low pass filtering is performed. After this the low pass filter is implemented for performing noise softening on ridges and for this convert orientation image into continuous vector filed. In BBVMFF continuous vector field has been obtained with its a and b components defined as $\phi_a(l,e) = \cos(2\theta(l,e))$ and $\phi_b(l,e) = \sin(2\theta(l,e))$. In BBVMFF, with the resultant feature vector field, the low pass filter with unity integral has been implemented where the size of filter decided is $Z_\phi \times Z_\phi$. The filter size of the a and b components are defined

$\phi_a'(l,e) - \sum_{m=-\frac{Z_\psi}{2}}^{\frac{Z_\psi}{2}} \sum_{n=-\frac{Z_\psi}{2}}^{\frac{Z_\psi}{2}} G_{Gaus}(m,n).\phi_a(l-mZ, e-nZ)$	**(5)**

$\phi_b'(l,e) = \sum_{m=-\frac{Z_\phi}{2}}^{\frac{Z_\phi}{2}} \sum_{n=-\frac{Z_\phi}{2}}^{\frac{Z_\phi}{2}} G_{Gaus}(m,n).\phi_b(l-mZ, e-nZ)$	**(6)**

Where $G_{Gaus}(m,n)$ represents the Gaussian function adopted.

The fingerprint orientation field has been estimated by mean of the following definition

$O'(l,e) = (1/2)tan^{-1}[\phi_b'(l,e)/\phi_a'(l,e)]$	**(7)**

Using Eq. 5 we estimated the core point. In BBVMFF, a circular region around the estimated core point was processed for tessellation with 80 sectors and the finger print ROI was identified with a circle of radius r pixels. In BBVMFF radius of the ROI is set to 100. The fingerprint ROI set is defined as

$\mathbb{P} = \{\mathbb{P}_1, \mathbb{P}_2, \mathbb{P}_3 \ldots \mathbb{P}_{\mathcal{P}}\}$	**(8)**

The fingerprint biometric image $\mathbb{p}_{\mathcal{P}}$ and the ROI identification of the fingerprint is shown in Fig. 3.

Fingerprint $\mathbb{p}_{\mathcal{P}}$ ***ROI* fingerprint $\mathbb{P}_{\mathcal{P}}$**

Fig. 3. Fingerprints ROI identification

4.4. *Gabor Phase and Magnitude Feature Extraction in BBVMFF*

In BBVMFF the use of Gabor kernels for phase and magnitude feature extraction from the multimodal ROI image datasets of Face and fingerprint is adopted. The use of Gabor definitions have proved to be effective in Face and fingerprint [19] biometric recognition systems. The Gabor kernels are complex band limited filters that enable fine grained localization in the frequency and spatial domain [20]. The Gabor kernels relate to the simple cells of the sensual visual cortex and thus are significant from the biological point of view as well [21]. Ability of the Gabor features to negate the biometric data acquisitions errors arising from illumination variations, intensity variations, position and orientations is an additional motivating factor for its adoption in the BBVMFF. Considering a predefined frequency band the Gabor kernels enable robust biometric definitions in terms of multi resolutional features, spatially local features and orientation features for verification mechanisms such as BBVMFF .The ROI images of the Face and fingerprint are down sampled to 128×128 prior to feature extraction[23][24].

Let $I^{ROI}(a,b)$ represent the down sampled biometric ROI image. Similar Gabor definitions are considered for the Face and fingerprint biometric data which enable a simple fusion discussed in the latter section. Consider the orientation is θ_o and the center frequency is F_s then the Gabor kernel is denoted as $\mathcal{K}_{s,o}(a,b)$. The feature extraction process in BBVMFF is achieved by performing the filtering operation on $I^{ROI}(a,b)$, utilizing the kernel function of size s and orientation o represented as $\mathcal{K}_{s,o}(a,b)$. The feature

$$_{BBVMFF}{}^{\mathcal{G}}FE(\mathbb{D}_n) = \mathcal{G}_{s,o}(a,b) = I^{ROI}(a,b) * \mathcal{K}_{s,o}(a,b) \quad (9)$$

extraction function $_{BBVMFF}{}^{\mathcal{G}}FE(\mathbb{D}_n): \mathbb{D}_n \in F \parallel P$ can be defined as

The features obtained $\mathcal{G}_{s,o}(a,b)$ are complex in nature i.e. $\mathcal{G}_{s,o}(a,b) = (\mathcal{G}_{s,o}^{r}(a,b) + \mathcal{G}_{s,o}^{i}(a,b)\, i)$. The real part is defined as $Re[I^{ROI}(a,b) * \mathcal{K}_{s,o}(a,b)]$ and the imaginary part is given by $Im[I^{ROI}(a,b) * \mathcal{K}_{s,o}(a,b)]$. On the basis of the computation resulting from $_{BBVMFF}{}^{\mathcal{G}}FE(\mathbb{D}_n)$, the phase definitions are obtained by $\Phi_{s,o}^{\mathcal{G}}(a,b) = arctan\left(\frac{\mathcal{G}_{s,o}^{i}(a,b)}{\mathcal{G}_{s,o}^{r}(a,b)}\right)$ and magnitude definitions by $M_{s,o}^{\mathcal{G}}(a,b) = \sqrt{\left(\mathcal{G}_{s,o}^{i\,2}(a,b) + \mathcal{G}_{s,o}^{r\,2}(a,b)\right)}$ .To achieve accurate feature definition of the biometric ROI images the BBVMFF adopts a Gabor kernel with $o = \{0,1,2,\dots,6,7\}$ and $s = \{0,1,\dots,4\}$ resulting in 40 complex Gabor filters. If T represents a transform operator then the magnitude feature vector $\mathcal{G}'$ obtained can be defined as

$$\mathcal{G}' = (\mathcal{G}_{0,0}^{T}, \mathcal{G}_{0,1}^{T}, \mathcal{G}_{0,2}^{T}, \dots, \mathcal{G}_{4,7}^{T})^{T} \quad (10)$$

4.5. *Bimodal Feature Fusion Algorithm*

The Gabor definitions of the Face and fingerprint biometric need to combined to construct the fusion set which incorporates the class label class label $\mathcal{P} = \{1,2,3 \dots \mathcal{F}\}$ required for classification and verification in the BBVMFF[23][24]. Considering the $\mathcal{P}^{th}$ user of the BBVMFF The fingerprint definition is represented as $\mathbb{F}_{\mathcal{P}}^{\mathcal{G}} = \{\mathcal{G}_{\mathcal{F}\mathcal{P}}' \cup \mathcal{G}_{\mathcal{F}\mathcal{P}}'\}$. By adopting a simple fusion technique the cumulative biometric definition of the $\mathcal{P}^{th}$user of the BBVMFF is defined as $_{BBVMFF}{}^{\mathcal{G}}FU(\mathcal{P})$

$$_{BBVMFF}{}^{\mathcal{G}}FU(\mathcal{P}) = \{\mathbb{I}_{\mathcal{P}}^{\mathcal{G}} \cup \mathbb{F}_{\mathcal{P}}^{\mathcal{G}}\} \quad (11)$$

4.6. *Dimension Reduction using LDA and Linear Projection*

For verification in the BBVMFF the fusion dataset points need to be projected into clusters. The data available in $\mathbb{B}$ is considered to encompass g points in C clusters. Each cluster represents a personnel $\mathcal{P} \in \mathcal{P}$ and is a subspace in the space $\mathbb{B}^{h}$. Let $\mathcal{G}_k$ represent the fused Gabor definition of the face, fingerprint and $\mathcal{G}_k \in \mathbb{B}^{h}$ then the individual data points to be projected can be represented as $\{(\mathcal{G}_k, c_k)\} \forall\, k \in h$. The class assignment variable is represented as $c_k \in \mathcal{P}$ in the data point[23][24].

Let the Gabor definition matrix represented as $\mathcal{G} \in \mathbb{B}^{h \times p}$ and is defined as $\mathcal{G} = \{\mathcal{G}_1, \mathcal{G}_1, \mathcal{G}_2, \dots \mathcal{G}_h\}$. In the BBVMFF the adoption of Fisher Scores and Linear Discriminant Analysis is considered for dimensional reduction of $\mathbb{B}$ .The Fischer scores computations [27] aid dimensional reduction and enable subspace projection optimization. The subspace projections are optimized by reducing the intra cluster distances and enhancing increasing the inter cluster The Linear Discriminant analysis in BBVMFF assists in feature combinations and enables accurate projections of the data points in the subspaces [28]. Let $\mathcal{D} \in \mathbb{B}^{r \times p}$ represent the dimensionally reduced matrix of dimensions $r \times p$. The matrix $\mathcal{D}$ can be considered as a collection of i row vectors i.e. $d^{i} \in \mathcal{D}$ or j column vectors i.e. $d_j \in \mathcal{D}$ .The projection of the matrix $\mathcal{D} \in \mathbb{B}^{p \times r}$ using linear discriminate analysis can be represented as a total scatter matrix $\mathcal{S}_T$. The scatter matrix $\mathcal{S}_T$ which is a sum of the between cluster scatter matrix i.e.$\mathcal{S}_b$and within cluster scatter matrix i.e. $\mathcal{S}_w$ is computed by $\mathcal{S}_T = \mathcal{S}_b + \mathcal{S}_w$. The between class cluster scatter matrix $\mathcal{S}_b$ is defined as

$$\mathcal{S}_b = \sum_{a=1}^{\mathcal{P}} h_a (m_a - m)(m_a - m)^{T} \quad (12)$$

4.7. *Classification Using K Nearest Neighbor*

The training set T is considered as the dataset of the registered $\mathcal{P}$ users in BBVMFI . Let the set is defined as $T = \{t_1, \cdots, t_{\mathcal{P}}\} \subset \mathbb{B}^{p \times r}$.The training vector $t_z = \{(\mathcal{G}_z, \mathcal{P}_z)\} \forall\, z \in \mathcal{P}$ where $\mathcal{G}_z$ is the Gabor biometric definitions of the face and finger print set representing the $\mathcal{P} \in \mathcal{P}$ class. Consider $U = \{u_1, \dots, u_y\} \subset \mathbb{B}^{p \times r}$ represent the unknown or testing dataset where $U \not\subset T$. Similar to the training set the testing set vector can be represented as $u_v = \{(\mathcal{G}_v, p_v)\} \forall\, v \in y$ with the class variable p_v is treated as an unknown which needs to be verified. The dimensionally reduced Gabor definition set of the training or testing sets is represented as $\mathcal{G}_x = \{\mathcal{G}_{1x}, \mathcal{G}_{2x}, \mathcal{G}_{3x}, \dots \mathcal{G}_{rx}\}$.

To verify the identity of the users in the unknown class U the use of Weighted K Nearest Neighbor Classifier is considered in BBVMFF. To classify the vectors $u_v \in U$ the Weighted K Nearest Neighbor ranks the Gabor biometric definitions of the test vector amongst the Gabor biometric definitions of the training vectors. Using the rank and the known $\mathcal{P}$ classes of the train data the classifier predicts the unknown user class of the test vector using the user classes of the similar neighbors. The similarity amongst the test and train vectors u_p, t_p is computed using

$$_{BBVMFF}^{Classify}Sm(u_p, t_p, w_p) = \left(\sum_{f=1}^{r}(w_{pf} \times t_{pf} \times u_{pf})\right) \times \left(\left(\sqrt{\sum_{f=1}^{r}(u_{pf})^2}\right)\left(\sqrt{\sum_{f=1}^{r}(t_{pf})^2}\right)\right)^{-1} \quad (13)$$

where w is the weight vector, r represents the total number of Gabor definitions of the face and fingerprint biometric under consideration.

V. PERFORMANCE EVALUATION

The BBVMFF proposed in this paper is developed on the Matlab platform. The biometric data of the frontal face and finger print from [22] is considered.

5.1. *SDUMLA-HMT multimodal biometric dataset*

The SDUMLA-HMT multimodal biometric dataset [22] is considered to evaluate the performance of the BBVMFF . The multi modal biometric dataset consists of biometric data of 106 users. In the SDUMLA-HMT dataset biometric data for 61 males and 45 female users is provided. The age group of the users varies from 17 years to 31 years. The SDUMLA-HMT data set provides biometric data of the frontal face, finger vein, iris, gait and finger print. To evaluate the BBVMFF performance. The frontal face and fingerprint biometric data is considered. The frontal face biometric data consists of varied facial expressions, poses, illumination conditions and wearable accessories like hats and glasses. The frontal face data consists of 84 images per user in the SDUMLA-HMT dataset. The fingerprint biometric data is acquired using 5 varied sensors is available. To classify the performance of BBVMFF fingerprint biometric data from the FT-2BU capacitive fingerprint scanner is considered. The finger print data of the middle finger, index finger, thumb finger for the left and right hand are provided. A total of 48 fingerprint biometric data per user is considered for performance evaluation presented here.

The dataset available is splited into training and testing infomation i.e. T, U. The testing data is used for verification. Equal number of train and test images are considered in the frontal face and fingerprint. The dataset used and the construction of the test and train data is summarized in Table 1.

Table 1: SDUMLA-HMT Data set Parameters Considered

Biometric Feature	***No of Users***	***Biometric Data Per User***	***Total Number Of Images***	***Training Data Size***	***Testing Data Size***
Frontal Face Biometric	*106*	*84*	*8904*	*4452*	*4452*
Finger Print (Left Hand + Right Hand)	*106*	*48*	*5088*	*2544*	*2544*

Table 2: Comparison Between Existing and Proposed Systems

System	Database Used	Techniques Used	Recognition Rate(%)
Existing	SDUMLA Dataset	Feature Level Fusion, Gabor Filter, PCA	92.20
	ORL Face & FVC 2002 Finger print database	Feature Level Fusion, Gabor Filter Bank	98.9
	FVC2004	Score Level Fusion, Gabor Filter, PCA	97.5
Proposed	SDUMLA-HMT Dataset	Feature Level Fusion, Gabor Phase and Magnitude features, LDA	99.4

Table 2 shows the comparison between existing and proposed systems. The proposed method is computationally efficient when compared to the existing approach .

VI. CONCLUSIONS

In the past decade the adoption of biometric verification systems have experienced a high growth rate. The unimodal biometric systems currently in place suffer from a number of drawbacks discussed in this paper. Multimodal biometric verification systems exhibit better reliability and robustness. This paper introduces a BBVMFF for multimodal verification systems. The performance of the BBVMFF is evaluated in the unimodal and Bi-modal mode using the SDUMLA-HMT multimodal biometric dataset. Based on the results presented in the performance evaluation the superiority of the BBVMFF when compared to the existing verification mechanisms in the unimodal and Bi-modal mode is proved. The future of the mechanism proposed is to scale and accommodate additional biometric traits for verification.

REFERENCES

[1] Poh N and Kittler J, "A Unified Framework for Biometric Expert Fusion Incorporating Quality Measures," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 34, no.1, pp. 3, 18, Jan 2012.

[2] Delac K and Grgic M, "A survey of biometric recognition methods," Electronics in Marine, *Proceedings of Elmar 2004. 46th International Symposium* , pp. 184, 193, 18-18 June 2004.

[3] Qinghan Xiao, "Security issues in biometric authentication," Information Assurance Workshop, *IAW '05. Proceedings from the Sixth Annual IEEE SMC* , pp. 8, 13, 15-17 June 2005.

[4] Rubenstein L Z, Solomon D H and Roth C P, "Detection and management of falls and instability in vulnerable elders by community physicians", *J. Am. Geriatr. Soc.*, 52, pp. 1527–1531, 2004.

[5] A Ross, K Nandakumar, and A K Jain, Handbook of Multibiometrics*, Springer*, 2006.

[6] Kumar A, Kanhangad V, Zhang D, "A New Framework for Adaptive Multimodal Biometrics Management," *IEEE Transactions on Information Forensics and Security*, vol. 5, no.1, pp. 92, 102, March 2010.

[7] A Ross and A K Jain, "Multimodal biometrics: an overview," *Proc.European Signal Processing Conference*, pp. 1221–1224, Vienna, Austria, Sept 2004.

[8] A K Jain and A Ross, "Multibiometric Systems", *Communications of the ACM*, Vol. 47, No. 1, pp. 34-40, 2004.

[9] DakshinaKisku, AjitaRattani, Phalguni Gupta, Massimo Tistarelli and JamunaKanta Sing, "Biometrics Sensor Fusion and its Applications", Ciza *Thomas (Ed.), ISBN: 978-953-307-101-5*, In Tech, Available from: http://www.intechopen.com/books/sensor-fusion-and-its-applications/biometrics-sensor-fusion.

[10] Conti V, Militello C, Sorbello F, Vitabile S, "A Frequency-based Approach for Features Fusion in Fingerprint and Iris Multimodal Biometric Identification Systems," *IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews,* vol. 40, no. 4, pp. 384, 395, July 2010.

[11] Fan Yang, Baofeng Ma, "A New Mixed-Mode Biometrics Information Fusion Based-on Fingerprint, Hand-geometry and Palm-print", *Fourth International Conference on Image and Graphics, ICIG 2007*, pp. 689, 693, 22-24 Aug 2007

[12] Teddy Ko T, "Multimodal biometric identification for large user population using fingerprint, face and iris recognition," *Applied Imagery and Pattern Recognition Workshop, 34th Proceedings*, pp. 6 pp. 223, 1-1 Dec 2005.

[13] Ravi S, Mankame, Dattatreya P, "Multimodal biometric approach using fingerprint, face and enhanced iris features recognition," *International Conference on Circuits, Power and Computing Technologies (ICCPCT*), pp. 1143, 1150, 20-21 March 2013.

[14] Shekhar S, Patel VM, Nasrabadi NM, Chellappa R, "Joint Sparse Representation for Robust Multimodal Biometrics Recognition," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 36, no. 1, pp. 113, 126, Jan.

[15] Zhenhua Chai, Zhenan Sun, Mendez-Vazquez H, Ran He, Tieniu Tan, "Gabor Ordinal Measures for Face Recognition," *IEEE Transactions on Information Forensics and Security,* vol. 9, no. 1, pp.14, 26, Jan 2014.

[16] Besbes F, Trichili H, Solaiman B, "Multimodal Biometric System Based on Fingerprint Identification and Iris Recognition," *International Conference on Information and Communication Technologies: From Theory to Applications, ICTTA 2008,* pp. 1, 5, 7-11 April 2008.

[17] Telgad R L, Deshmukh P D and SiDDiQUI A M N", Combination approach to score level fusion for Multimodal Biometric system by using face and fingerprint ", *Recent Advances and Innovations in Engineering (ICRAIE),,* pp1-8, 9-11 May 2014.

[18] Deshmukh A,Pawar S and Joshi M", Feature level fusion of face and fingerprint modalities using Gabor filter bank",*IEEE International Conference on Signal Processing,Computing,Control,* pp1-5, 26-28 Sept. 2013.

[19] Weitao Li, Kezhi Mao, Hong Zhang, Tianyou Chai, "Selection of Gabor filters for improved texture feature extraction," *17th IEEE International Conference on Image Processing (ICIP)*, pp. 361, 364, 26-29 Sept 2010.

[20] Chengjun Liu, Wechsler H, "Gabor feature based classification using the enhanced fisher linear discriminant model for face recognition," *IEEE Transactions on Image Processing,* vol. 11, no. 4, pp. 467, 476, Apr 2002.

[21] J G Daugman," Uncertainty relation for resolution in space spatial frequency and orientation optimized by two-dimensional visual cortical filters" *JOSA A*, 2(7):1160–1169, July 1985.

[22] Yilong Yin, Lili Liu, and Xiwei Sun. "SDUMLA-HMT: A Multimodal Biometric Database." *The 6th Chinese Conference on Biometric Recognition (CCBR 2011),* Lecture Notes in Computer Science 7098, pp. 260-268, Springer Berlin Heidelberg, 2011.

[23] Manjunathswamy B E, Thriveni J, K. R. Venugopal, L. M. Patnaik, "MultiModel Personal Authentication Using Finger Vein and Iris Images(MPAFII)", *Fifth International Conference on Advances in Computer Engineering-ACE*, at Kochi, India, December 26-27, 2014.

[24] Manjunathswamy B E, Thriveni J, K. R. Venugopal, L. M. Patnaik, "MultiModel Personal Authentication Using Finger Vein and Face Images(MPAFFI)", *Third International Conference on Parallel, Distributed and Grid Computing-PDGC*, at Waknaghat, Solan, Himachal Pradesh, India, December 11-13, 2014.