# Multimodal Biometric System Using Finger Knuckle and Nail: A Neural Network Approach

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***Abstract*—Dorsum of the hand can be very useful in Personal identification but yet it has not that much extensive attention. Single scan of dorsum hand can give two biometric traits finger-knuckle and finger nail. This paper presents an approach to combine Finger-knuckle and finger-nail features. Finger nail biometric is considered as quite unique biometric trait hence we combine this trait with finger knuckle. We also developed an algorithm to extract ROI from Finger-knuckle and finger-nail. Finger-knuckle features are extracted using Mel Frequency Cepstral Coefficient (MFCC) technique and the features of finger-nail are extracted from second level wavelet decomposition. We combined these features using feature level fusion and feed forward back-propagation Neural Network for classification. The performance of the system has been tested on our own KVKR- knuckle database that includes 100 subject's dorsal hands. Evaluation results shows that increase in training set gives increased performance rate. The best performance of the proposed system reaches up to 97% with respective training of 90% of total dataset.**

***Index Terms*—multimodal biometric, finger-knuckle, finger-nail, MFCC, backpropagation neural network**

## I. INTRODUCTION

It is more important to identify spoof person or unknown criminals at any crime. Therefore, it is crucial to utilize the latest human identification techniques. Each person has his/her own unique characteristic that remains unchanged throughout life, sometime after death. Dorsal aspect of human hand is having many unique features [1], like top knuckles, middle knuckles, base knuckles, hand veins shape or nail shape. The joint from phalanx bones of human hand generate distinct texture patterns on the finger back surface also known as dorsum of the hand [2] Fig. 1 shows the dorsal of hand.

Knuckle features are considered unique and finger-nail features are considered as distinct as others and hence somewhat useful for identification purposes. Thus in this research work knuckle biometric traits are being used and fingernail is used as supportive biometric traits because it is less accurate. Finger-Knuckle-Print and Fingernail identification can plays an important role in crime scene. The texture pattern produced by the finger knuckle bending is highly unique [3] and [4]. Finger-knuckle-prints (FKP), which refers to the inherent skin patterns of the outer surface around the phalangeal joint of one's finger, is a new member of the biometrics family. It has high capability to discriminate different individuals [5]. Fingernails have been proposed as a means of personal identification by a number of researchers. Human fingernails bear longitudinal ridges on both their upper surfaces [6] and [7]. As per literature survey and available information we find four main shape were identified that are broad and square, short wide nail, almond shaped nail, very small square nails [8] following Fig. 2 show a general nail shape.

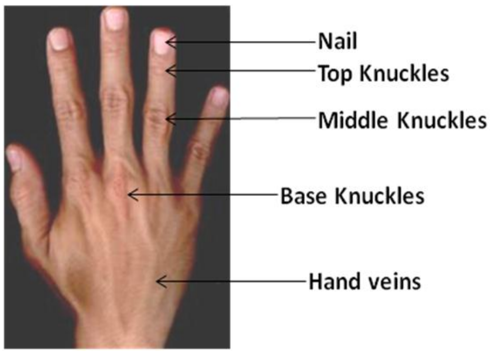


Figure 1. Dorsal aspects of human from KVKR-knuckle database.

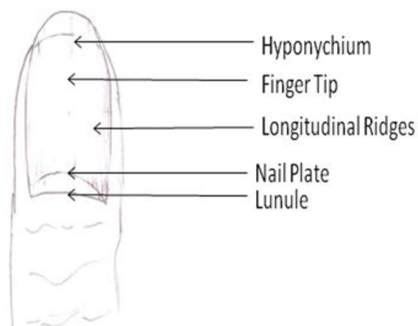


Figure 2. General nail shape.

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## II. Proposed Work

The main need of biometric era is that improve the performance of biometric system with minimum iteration of time. To improve the performance of biometric system, nowadays researchers prefer the multiple modalities for recognition on the basis of score level as well as feature level. In our research we proposed the new view of biometric that a hand based biometric on the basis of finger knuckle and fingernail. We concentrate on four dorsal fingers except thumb. The finger-knuckle and finger-nail extracted on the basis of ROI Extraction algorithm. The performance of the system is varying on the database quality so, to improve the quality of the images, enhancement has been done. In the proposed multimodal biometric recognition system we extract the feature of finger knuckle using Mel Frequency Cepstarl Coefficient and fingernail using wavelet decomposition. The flow of the proposed system is detailed is shown in Fig. 3.

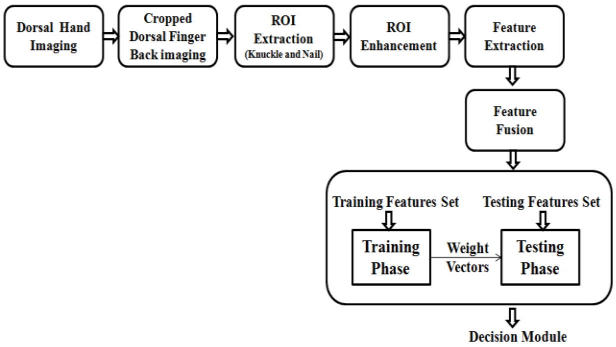



Figure 3. Working flow of proposed multimodal biometric system.

## III. ROI Extraction

At preprocessing step we have used orientation based algorithms to decide Region of Interest (ROI). Basically dorsal surface of the hand having many key features like Knuckle crease, fingernails longitudinal ridges, nail lunule shape and Hand vein have been used for verification. At the first stage of preprocessing we crop manually four indexes, middle, ring and little fingers from dorsal hand surface. This has been shown in Fig. 4.

Figure 4. Index, middle, ring and little fingers from dorsal hand.

ROI of finger knuckle and finger nail extracted from cropped finger, to extract Knuckle region we first decide reference point on cropped single finger image where maximum knuckle crease oriented. The knuckle image represents oriented texture and has very rich structural information within the image. Orientation of crease appear in cropped dorsal finger image is large in middle knuckle of each finger. Local crease orientation is usually specified for a block rather than at every pixel [9] and [10].

Local crease orientation at pixel [x, y] is the angle $\theta_{xy}$ that the knuckle crease, crossing through an arbitrary small neighbourhood centred at [x, y], that form with the horizontal axis. Gradient base approach is a simple and most used approach. Hence to calculate creases appear in dorsal finger image, we used gradient base approach. Divide image in non-overlapping block of size W x W. In this proposed method, W is set equal to 17.Compute the gradient of each pixel. The gradient $\nabla(x, y)$ at pixel of image I is a two domination vector [dx(u,v), dy(u,v)]. We compute crease orientation using using following equation.

$$
\begin{aligned}
G_{xy} &= \sum_{h=k=-8}^{8} \nabla_x\left(x_i+h, y_j+k\right) \nabla_y\left(x_i+h, y_j+k\right) \\
G_{xx} &= \sum_{h=k=-8}^{8} \nabla_x\left(x_i+h, y_j+k\right)^2 \\
G_{yy} &= \sum_{h=k=-8}^{8} \nabla_y\left(x_i+h, y_j+k\right)^2
\end{aligned}
\tag{1}
$$

where $a\tan 2$ is four-quadrant inverse tangent ($2G_{xy}$, $G_{xx}$–$G_{yy}$), we consider maximum orientation of each block of size WxW and decide maximum oriented pixel of that block as reference point to crop ROI of knuckle print. The reference point and cropped knuckle ROI are shown in Fig. 5. During this process we found that extraction of ROI this algorithm is slightly incorrect for less informative dorsal hand to extract ROI of knuckle. On the other hand of ROI extraction of fingernail we go through some steps firstly we smooth the given Image by applying Gaussian low pass filter, than image is converted in binary form by using mean value of filtered image as a threshold T.

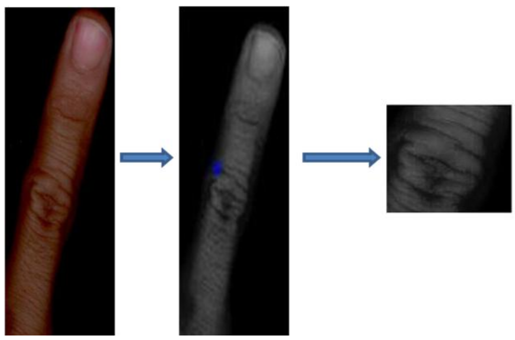


Figure 5. Cropped knuckle ROI using reference point.

A threshold T is applied to the smooth image. The points whose values greater than T are set to one as foreground while the remaining data are set to 0 as background. The process of fingernail ROI extraction from finger is shown in Fig. 6.

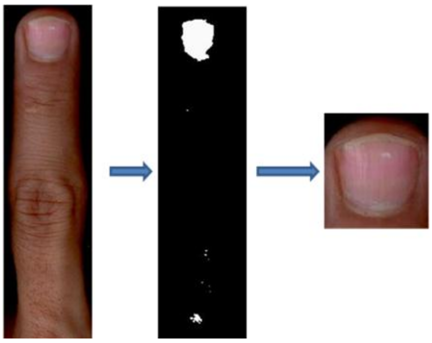


Figure 6. Finger-nail ROI extraction.

The sample ROI extracted from four index, middle, ring and little fingers are shown in Fig. 7.

Figure 7. Cropped ROI of Four index, middle, ring and little fingers.

Once we extract ROI of fingernail and finger middle knuckle from all four fingers we further go for enhancement and feature extractions as shown.

## IV. Feature Extraction

### A. Feature Extraction of Fingknuckle

In this paper we are used wavelet transformation for the image to one dimensional signal conversion. The wavelet transformation also used for dimension reduction in signal processing. The converted finger –knuckle image to signal is shown in Fig. 8.

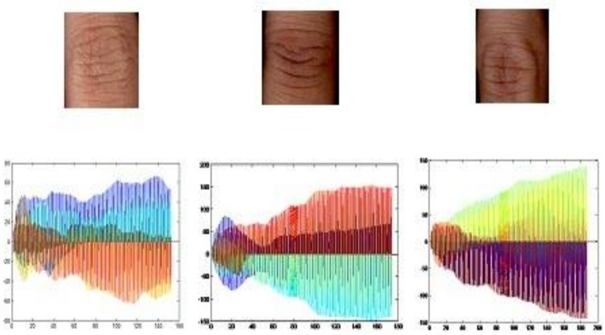
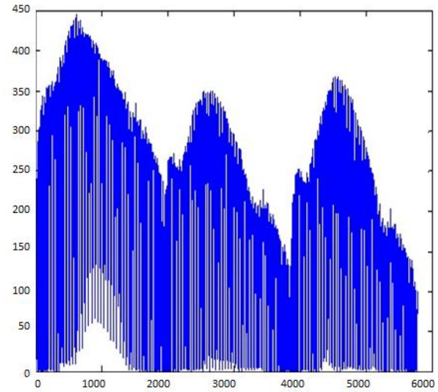


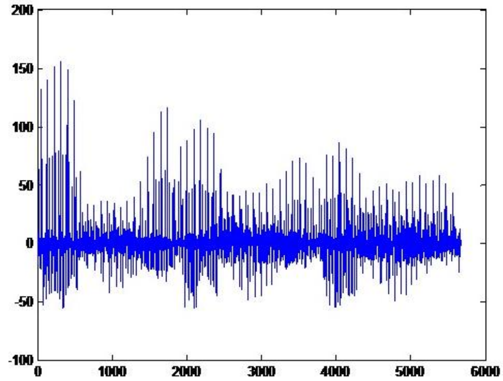
Figure 8. Converted finger knuckle image to signal.

The input knuckle image is decomposed by using the DWT. For level 1, numbers of sub bands are 4 and 3 sub bands are added for each next level. Thus the increase in levels of DWT increases the features.

### B. Feature Extraction of Fingernail




(A)




(B)

Figure 9. (A) The detail coefficient (B) Approximation coefficients of fingernail using wavelet decomposition

The finger-nail having morphological feature such as shape, size and angle of curve but as the feature varies as per age group so, in this paper we are concentrate on basic decomposable feature. Pre-processed fingernails decompose using wavelet up to second level. After wavelet decomposition we get approximation as well as detail feature set, from approximation and detail feature set we concatenate the both feature in single scale feature using mean operation. The difference in detail level features as well as approximation level feature is shown in Fig. 9.

## V. Fusion Strategies

The Feature level fusion integrates the feature set of multiple modalities of biometric. In this paper we used two modalities of biometric finger knuckle and fingernail. Let F= $\{f1, f2, f3, f4, f5, f6..........fn\}$ be an extracted feature of finger knuckle using MFCC and S=$\{s1, s2, s3, s4, s5, s6........sn\}$ is an extracted feature of finger nail using wavelet decomposition. The fused feature vector is X= $\{x1, x2, x3, x4, x5, x6........xn\}$ obtained by augmenting normalize feature vector and performing feature selection on resultant fused feature vector. Features extracted from finger knuckle and fingernails are combining using feature level fusion scheme, this feature level fusion is performed by concatenating the two feature sets. Using MFCC of finger knuckle we got single feature vector of size 12x1 and feature set of fingernail having 2x1 in size and fusion of this two vectors we got 14x1 single feature vector.

## VI. Neural Net as Classifier

We choose Multi-Layer Perceptron (MLP) with a back propagation learning algorithms for the proposed system. The MLP neural network has feedforword architecture within input layer, a hidden layer, and an output layer [11]-[14]. During first stage of weights initialization some small random value are assigned. Each input unit receives the input signal $x_i$ and forward towards hidden layer. Hidden layer sums its weighted input signals as,

$$y_{in} = b + \sum_{i=1}^{n} x_i v_{ij} \tag{2}$$

where $y_{in}$ is response of output unit, $b$ is a bias, $x_i$ is a input training vector and $v_{ij}$ is a bias on hidden unit j. Relative activation function is

$$Z_j = f(y_{in}) \tag{3}$$

And it sends signals towards output layer. During the back propagation stage error is calculated as,

$$\delta_k = (t_k - y_k) f(y_{in}) \tag{4}$$

where $t_k$ output target vector and $y_k$ is output unit $k$. Each hidden unit sums its delta inputs from units in the layer above as.

$$\delta_{in} = \sum_{k=1}^{m} \delta_j w_{jk} \tag{5}$$

where $\delta_j$ is error at hidden unit, $w_{jk}$ is weights at hidden layer. Whereas error is calculated as,

$$\delta_j = \delta_{in} f(y_{in}) \tag{6}$$

At the end each output unit updates its bias and weights as,

$$w_{new} = w_{old} + \Delta w_{ij}$$

$$b_{new} = b_{old} + \Delta b_{ij} \tag{7}$$

where $w_{new}$, $b_{new}$ are new weights and new bias $w_{old}$, $b_{old}$ are old weights and old bias and $\Delta w_{ij}$ and $\Delta b_{ij}$ are weight correction and bias correction respectively. The stopping condition is error minimization

## VII. Experimental Result

We have collected dorsal hand images from 100 subjects using a HP Color Laser Jet CM1312 MFP Series PLC6 low cost scanner in our Multimodal biometric laboratory. Generally all subjects were from Dept of CS and IT, Dr. B. A. M. University campus, having age group between 22 to 25 years. Each subject provided three images of right dorsal hand and three images of left dorsal hand. Time gap between collecting second and third impression were 10 days. Hence we had database (100x3 Right dorsal hands and 100x3 left dorsal hands) images. So, our database (called KVKR-Knuckle) consists of a total of 600 dorsal hand images. We conduct extensive experiments to evaluate the effectiveness and robustness of the proposed system. We presented an algorithm to extract ROI of finger knuckle and finger nail. Once the training is completed, we have to check the network performance. The validation performance reached at minimum iteration 18 which has been shown in figure (10). The training process has been stopped at 24 epochs, i.e. 6 more iteration before the training stopped. The validation and test curves are very similar hence performance is high. If the test curve had increased significantly before the validation curve increased, then it is possible that some over fitting might have occurred. The best validation performance of multimodal biometric system is shown in Fig. 10.

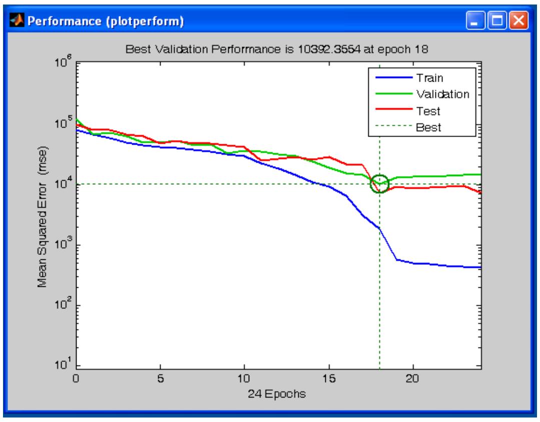



Figure 10. Best validation performance of proposed multimodal biometric system.

The next step in validating the network is to create a regression plot, which shows the relationship between the outputs of the network and the targets. Here we can see network outputs and the targets are nearly equal hence we can say that performance of our system is high. The result is shown in the following regression plot Fig. 11.

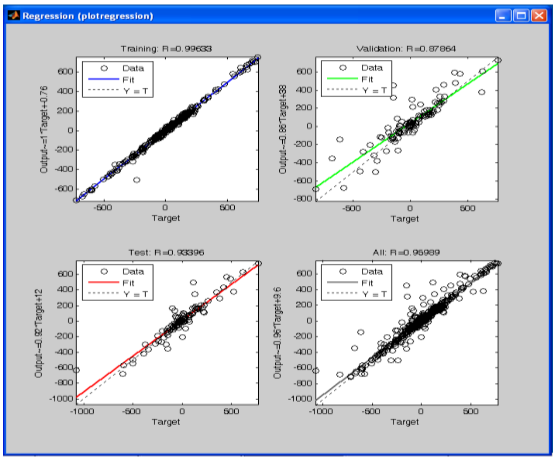



Figure 11. Regression plot represent the training, validation, testing and all data.

The four axes represent the training, validation, testing and all data. Where dotted line show the perfect results that show the output equal to target. The solid line represents the best fit linear regression line between outputs and targets. The R value is an indication of the relationship between the outputs and targets. If R = 1, this indicates that there is an exact linear relationship between outputs and targets. If R is close to zero, then there is no linear relationship between outputs and targets. In above figure training axes having Value R=0.996 which is near to 1 and also in axes validation, test and all having value R= 0.878, 0.933, 0.959 respectively which are also near to 1 hence results indicates strong linear relationship between the targets and outputs. Following Table I describe the detail of training validation as well as accuracy. If the training sample increases definitely accuracy increase with some difference increment of time.

TABLE I. THE COMPARATIVE STRUCTURE OF ACCURACY

| **Training (%)** | **Validation (%)** | **Testing (%)** | **No. Of Hidden Layers** | **Time elapsed (second)** | **Accuracy (%)** |
|---|---|---|---|---|---|
| 70 | 10 | 30 | 25 | 4 | 85 |
| 80 | 15 | 35 | 20 | 5 | 89 |
| 90 | 5 | 50 | 15 | 7 | 97 |

## VIII. CONCLUSION

Multimodal biometric systems are found to be more reliable, robust and accurate systems as compare to unimodal biometric systems. The fusion at feature level can give more accurate results than score level and decision level due to the less information at these levels, but fusion at feature level found to be difficult. In this work we have done fusion of finger-knuckle and fingernail at feature level. The features extraction from finger-knuckle and fingernail are performed using MFCC coefficient. The performance of the system 97%, for the training 90% with time slice of 7 second.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