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Feature Level Fusion of Seven Neighbor Bilinear Interpolation Data Sets of Finger Vein and Iris for Multimodal Biometric Recognition

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ABSTRACT

Biometric systems are ruling the security industries nowadays, by using Biometric traits of individual; authentication of a person is done. Biometric traits will be degraded as the age of the person increases. So we cannot depend on only one biometric trait, since person finger print may be degraded over the time, face shape may be changed over the age etc. In order to overcome such problems Multimodal biometric trait are used, so multiple traits are used to identify a person. And also by using Multimodal biometric, recognition rate will so be improved. Using Multimodal biometric obviously we get more than one feature combinations which can be used separately or with different fusion technique these features may be combined. In the Proposed work, Features of iris and finger vein biometric are combined using feature level fusion. New Feature level fusion Framework design is introduced, in this framework SDUMLA-HMT Database of finger vein and iris, Machine Learning and Data Mining Lab, Sha ndong University is used for experimentation. Initially Seven Neighbor Bilinear Interpolation method is applied on finger vein and iris data samples and feature level fusion of new method is identified by combining uniform local binary pattern (ULBP) features of Seven Neighbor Bilinear Interpolated (SNBI) data sets of Finger vein and Iris. Ensemble subspace discriminant classifier is used for experimentation, excellent recognition rate results obtained from experiment. We also identified that classification accuracy is very much increased when compared with normal uniform binary pattern fusion against Seven Neighbor Bilinear Interpolated data sets fusion.

Key words: Feature Level Fusion, Multimodal biometric, Seven Neighbor Bilinear Interpolation (SNBI), Uniform Local Binary Pattern (ULBP).

1. INTRODUCTION

Biometric identification system will make use of Biometric traits like face, finger, iris, gaits and finger veins etc. to recognize or identify individuals. Biometric traits recognition system considerably increases research interest form past decades. Biometrics like Finger vein and iris will remain unchanged in a person for a long period of time, so recognition can be done for a long period of time without updating the database. And also if we see the past research history we can observe that not many work is done using iris and finger vein biometric traits. High recognition rate can be achieved by using face and fingerprint traits, but we need to capture the data sets with high precision care, if data collected are not properly that is quality is not maintained while collecting images then results will be very poor. In order to overcome this type of situation finger vein and iris can be used for biometric recognition.

Even though many of the research has carried out and lot of robust system has developed forging of biometric traits is very difficult to avoid. Person outer surface biometric traits like Finger print; face etc. can be easily forged. So by using Inner layer biometric traits like finger vein structure, iris etc. forging can be avoided very easily since they cannot be manipulated. Lot of biometric recognition systems available in the market is unimodal systems. In uimodal systems only one biometric traits are used for person identification, were chances of rejection rate is more because for example if device consider only finger print then person finger may not identified because of improper positioning of finger on scanner or sweaty finger. In this situation even though person is genuine it is rejected. By using multimodal biometric systems we can decrease rejection rate also we can increase acceptance accuracy [1].In this proposed work Uniform Local Binary Pattern features are fused.

This paper is organized as follows: In chapter 2, literature survey of various work done on finger vein and iris biometrics. In chapter 3, seven neighbor interpolation techniques for image enhancement is discussed, in chapter 4, Databases used for experiment is shown, in chapter 5, feature extraction methods are discussed, in chapter 6, New Feature level fusion Framework design is introduced followed by the experimentation of case studies and result evaluations in section 7. The conclusions are discussed in section 8.

2. LITERATURE REVIEW

More research is going on nowadays on multimodal systems, these systems are introduced to improve efficiency of identification and to furnish more security [10]. Shruthi et al. introduced combination of finger print and vein at score level fusion which is nonlinear fusion, the nonlinear approach gave better result [2]. Multimodal biometrics of face and iris features gave more accurate results when compared with unimodal systems, which was discussed by Chen et al [3]. All the different levels of fusion level with finger print, face and iris biometrics are implemented and showed overall improvement of result by Ko et al.[4]. The Identification of stability area of finger vein was the challenging. If we consider low stability area then while template matching is not possible, so in order to identify stability area of the finger vein Darun et al. introduced occurrence probability matrix (OPM). This OPM identified higher stability areas which contribute for person identification [5]. For all the three month babies the development of iris will start, and for all the baby's unique pattern will be formed when they are at the age of twelve months. This unique pattern is different from each individual.

Since it is the internal part of the body it will be more secured and not possible to forge from any one, Iris recognition systems are non-nosy in nature [6].

From the Literature Survey it has been observed that since finger vein and iris are the internal part of the body they are more secured biometrics and forging is not possible and also from the literature it has been proved that finger vein and iris can be used for biometric recognition, and also multimodal biometrics will considerably improve the overall biometric identification/recognition results. And also work done so far are concentrated on various biometric combinations, very few work is carried out with the combination of finger Vein and iris biometrics, and for multimodal biometric fusions technique seven neighbor bilinear interpolation [8] features are not used yet.

3. SEVEN NEIGHBOR BILINEAR INTERPOLATION FOR IMAGE ENHANCEMENT

Image interpolation mean resize of image to higher level without losing its quality or resolution of an image. Using seven neighbor interpolation technique [8], image resolution is for data base samples of finger vein and iris. So that we can use more detailed features for fusion.

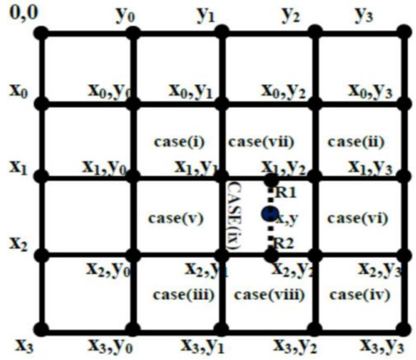

Figure 1: Seven Neighbor bilinear interpolation

There interpolation techniques applied to images may cause unfocused edges and loosing photo info. To have improvement in interpolation, we advanced a changed seven neighbor bilinear interpolation which increases smoothness and give better quality images.

3.1 Seven Neighbor Function

Function OUTΔP, ΔQ (RGB) = 7N (IN P,Q(RGB))
/*INP,Q(RGB) input image of dimension PXQ along 3 colour planes. OUTΔP, ΔQ(RGB) up sampled image of dimension ΔPXΔQ along 3 colour planes with an interpolation factor Δ.*/

Begin
m = 1 to ΔP increment by step 1
n = 1 to ΔQ increment by step 1

$$x = \frac{m}{\Delta}\ y = \frac{n}{\Delta}$$

$$x_1 = \left\lfloor\frac{m}{\Delta}\right\rfloor\ x_2 = \left\lceil\frac{n}{\Delta}\right\rceil\ y_1 = \left\lfloor\frac{n}{\Delta}\right\rfloor\ y_2 = \left\lceil\frac{n}{\Delta}\right\rceil$$

/*Applying bilinear interpolation on pixels (x_1,y_1), (x_1,y_2), (x_2,y_1) & (x_2,y_2)*/

$$R_1 = IN_{x_1,y_1}(RGB) + \left(\frac{(y-y_1)}{(y_2-y_1)}\right) * (IN_{x_1,y_2}(RGB) - IN_{x_1,y_1}(RGB))$$

$$R_2 = IN_{x_2,y_1}(RGB)) + \left(\frac{(y-y_1)}{(y_2-y_1)}\right) * (IN_{x_2,y_2}(RGB) - IN_{x_2,y_1}(RGB))$$

$$Res1_{x,y}(RGB) = R_1 + \left(\frac{(x-x_1)}{(x_2-x_1)}\right) * (R_2 - R_1)$$

$\partial x = x - x_1 \& \partial y = y - y_1$

if ($\partial x < 0.5$ and $\partial y < 0.5$) //case (i) of Fig. 3

$$f(x_1, y_1) = \frac{\sum_{i=0,1}\sum_{j=0,1}(x_i y_j)}{4}$$

if($\partial x < 0.5$ and $\partial y > 0.5$) //case (ii) of Fig. 3

$$f(x_1, y_2) = \frac{\sum_{i=0,1}\sum_{j=2,3}(x_i y_j)}{4}$$

if (($\partial x > 0.5$ and $\partial y < 0.5$) //case (iii) of Fig. 3

$$f(x_2, y_1) = \frac{\sum_{i=2,3}\sum_{j=0,1}(x_i y_j)}{4}$$

if (($\partial x > 0.5$ and $\partial y > 0.5$) //case (iv) of Fig. 3

$$f(x_2, y_2) = \frac{\sum_{i=2,3}\sum_{j=2,3}(x_i y_j)}{4}$$

/* A
pplying bilinear interpolation on altered surrounding pixels (x1,y1) (x1,y2) (x2,y1) & (x2,y2) and store result in Res2x,y(RGB)* shown in Figure 1. /

$$R_1 = IN_{x_1,y_1}(RGB) + \left(\frac{(y-y_1)}{(y_2-y_1)}\right) * (IN_{x_1,y_2}(RGB) - IN_{x_1,y_1}(RGB))$$

$$R_2 = IN_{x_2,y_1}(RGB)) + \left(\frac{(y-y_1)}{(y_2-y_1)}\right) * (IN_{x_2,y_2}(RGB) - IN_{x_2,y_1}(RGB))$$

$$Res2_{x,y}(RGB) = R_1 + \left(\frac{(x-x_1)}{(x_2-x_1)}\right) * (R_2 - R_1)$$

/* Fuse the results with max filter and store at interpolated pixel coordinates of output image */
End /* Function Ends */

By using seven neighbor interpolation function image resolutions of data base samples are increased to ratio of 1:2

$$OUT_{m,n}(RGB) = max(Res1_{x,y}(RGB), Res2_{x,y}(RGB))$$

and 1:4 with respect to the input database images. Output of this function is used to generate two times increased size of one data base and four times increased size of another database. Finally we obtain 1:2 ratio increased and 1:4 ration increased data bases of finger vein and iris data base.

4. DATABASE USED FOR EXPERIMENTATION

4.1 The Database of Finger Vein and Iris

Database Taken from the Machine Learning and Data Mining Lab, Shandong University (SDUMLA)[7]. This data base includes five biometric traits that is face, finger, vein, gait, fingerprint and iris which is called as SDUMLA-HMT Database. SDUMLA-HMT Database is available for free, so that researchers can use it without paying. This is freely available in order to promote biometric research.

A. Finger Vein data sets

Total of around 3,816 images are available in database which contains samples of index finger, middle finger and ring finger of both hands with 6 repeated samples. Size of the image is 320X240 pixels stored in .bmp format as shown in Figure 2.

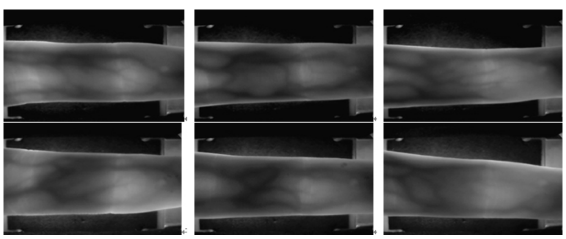

Figure 2: Finger Vein SDUMLA-HMT Database sample images.

We considered 6 left index finger veins of 40 persons for our experimentation, folders are named as 1 to 40 which means person 1 to person 40, and each folder consists of 6 samples 1 to 6, that is 6 left index finger vein of each person respectively.

B. Iris data sets

Total of around 1,060 images are available in database which contains samples of 5 images of both left and right iris, total of 10 images of each person. Size of the image is 768X576 pixels stored in .bmp format as shown in Figure 3.

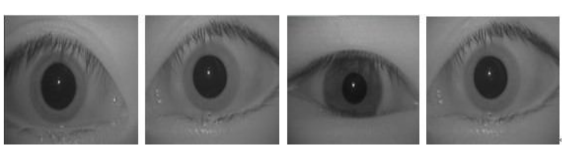

Figure 3: Iris SDUMLA-HMT Database sample images

We considered 3 sets of left and right iris of each person that is total of 6 iris images of each person. Folders are named as 1 to 40 which means person 1 to person 40, and each folder consists of 6 samples 1 to 6, that is 3 left iris and 3 right iris of each person respectively.

5. FEATURE EXTRACTION

In the proposed work we considered Local Binary Pattern (LBP) features for a given input image[11], LPB features has an advantage over others because it provides a homogeneous feature vector output for all the given input image. We can reduce the size of feature vector by considering uniform local binary patterns (ULBP), which returns 59 feature vectors. For both finger vein and iris ULPB function is applied and 59 features are obtained. Since both finger vein and iris features are homogenous and contains 59 features, they can be easily combined together using fusion techniques.

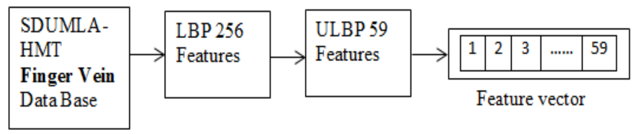

Figure 4: Feature Extraction from Finger Vein data samples

Finger vein feature extraction of both 1:2 and 1:4 ratio databases is obtained with the same procedure as shown in the Figure 4. Both the data samples will return uniform binary pattern 59 features for each sample.

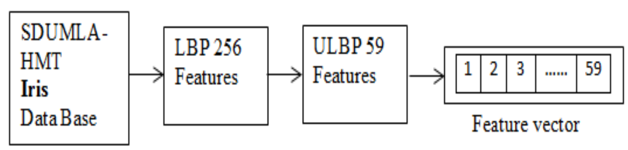

Figure 5: Feature Extraction from Iris data samples.

Iris feature extraction of both 1:2 and 1:4 ratio databases is obtained with the same procedure as shown in the Figure 5. Both the data samples will return uniform binary pattern 59 features for each sample.

6. PROPOSED ARCHITECTURE

This paper presents novel feature level fusion by selecting a SNBI increased ratio feature of finger vein and Iris data base. The novel framework showed in the Figure 6 and Figure 7 for both unimodal and multimodal biometrics.

Finger vein and iris data base are taken from SDUMLA-HMT database both finger vein and iris data samples are passed on seven neighbor interpolation function discussed in chapter 3. After applying SNBI for both the database, four individual databases each two of 1:2 ratio and 1:4 ratio is obtained as shown in Figure 6. All four data bases are trained and tested separately using ensemble subspace discriminant classifier.

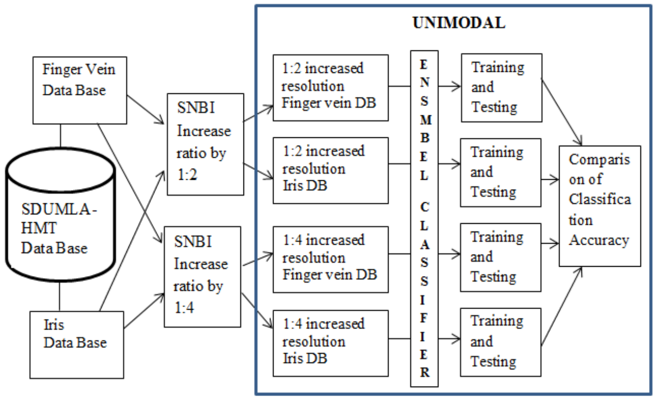

Figure 6: Unimodal Framework

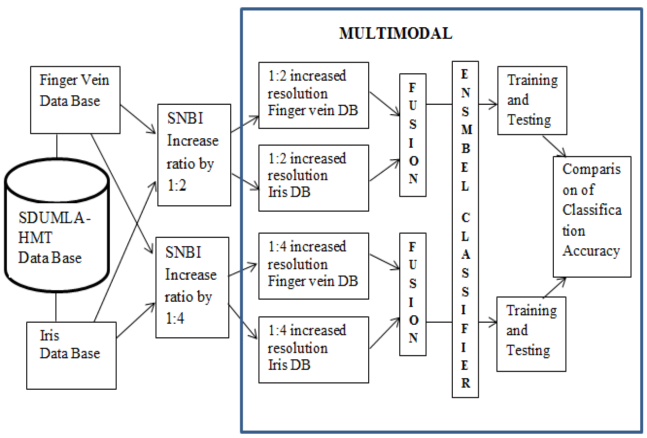

Figure 7: Proposed research work modal for feature level fusion

In proposed work of multimodal biometric obtaining four data bases after applying SBNI, fusion of features are carried out [9]. 1:2 increased resolution Finger vein DB is fused with 1:2 increased resolution Iris DB and 1:4 increased resolution Finger vein DB is fused with 1:4 increased resolution Iris DB, both fused data samples are trained and tested using ensemble subspace discriminant classifier as shown in Figure 7.

6.1 Fusion technique

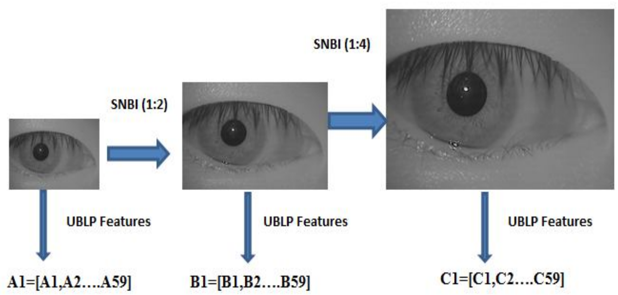

Figure 8: Iris SNBI ULBP features representation

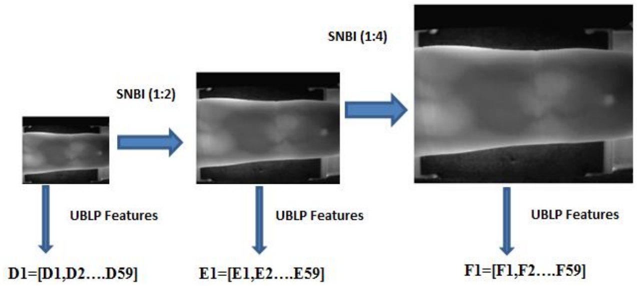

Figure 9: Vein SNBI ULBP features representation

The proposed algorithm represents the extraction of features from both SDUMLA-HMT data sets and SNBI datasets; fusion technique [9] is applied to ULBP features of SNBI and standard data sets. Ensemble Subspace discriminant classifiers is used for training and testing.

6.2 Fusion of Multimodal Finger Vein and Iris ULBP Features of 1:4 SNBI Data Samples

$$\text{SNBI IRIS UBLP features: } C = \begin{pmatrix} 1{:}\,C1, C2 \ldots.C59 \\ 2{:}\,C1, C2 \ldots.C59 \\ 3{:}\,C1, C2 \ldots.C59 \\ . \\ . \\ . \\ 200{:}\,C1, C2 \ldots.C59 \end{pmatrix}$$

$$\text{SNBI Finger Vein UBLP features: } F = \begin{pmatrix} 1{:}\,F1, F2 \ldots.F59 \\ 2{:}\,F1, F2 \ldots.F59 \\ 3{:}\,F1, F2 \ldots.F59 \\ . \\ . \\ . \\ 200{:}\,F1, F2 \ldots.F59 \end{pmatrix}$$

Concatenation of 1:4 SNBI
IRIS and Finger Vein data Samples:

$$[C\ F] = \begin{pmatrix} 1{:}\,C1, C2 \ldots.C59\ F1, F2 \ldots.F59 \\ 2{:}\,C1, C2 \ldots.C59\ F1, F2 \ldots.F59 \\ 3{:}\,C1, C2 \ldots.C59\ F1, F2 \ldots.F59 \\ . \\ . \\ . \\ 200{:}\,C1, C2 \ldots.C59\ F1, F2 \ldots.F59 \end{pmatrix}$$

The above matrix shows the fusion of SNBI ULBP feature for 1:4 ratio finger vein and iris data samples. Similarly for 1:2 ratio data samples fusion is carried out, ratios of images as shown in Figure. 8 and Figure. 9. Unimodal and Multimodal finger vein and iris fusion is explored and results and graphs are plotted in the Table 1, 2 & 3, Figure 10 & 11.

7. CASE STUDY OF MULTIMODAL BIOMETRICS: FINGER VEIN AND IRIS

We Considered SDUMLA-HM finger vein and iris data samples, And Mapped as finger vein first sample to iris first sample as person 1, finger vein second sample to iris second sample as person 2. Same mapping is carried out for all 40 persons , each person have 6 sample , So finally 240 multimodal data samples of finger vein and iris are collected. SNBI technique is applied for original data base and new data database created finger vein and iris separately. Features are extracted from finger vein and iris for all 6 data bases are two standard data base, two 1:2 ratio increased data base and two 1:4 increased data database, fusion method like concatenation is applied to finger vein and Iris features, which gives 240*119 feature vector for concatenation. For Training three, four & five samples of 40 persons that is 120*119, 160*119 and 200*119 respectively is input to Ensemble subspace discriminant model, and testing of remaining samples of same combinations 40 persons are used.

7.1 Procedure of execution for three sample training and three sample testing

A. UBLP features of finger vein are extracted from first three samples of required data base (out of 6 databases). Since UBLP gives 59 features in a single row, for all 40 person first three samples will return 120 rows and 59 column feature table.

B. UBLP features of Iris are extracted from first three samples of required data base (out of 6 databases). Since UBLP gives 59 features in a single row, for all 40 person first three samples will return 120 rows and 59 column feature table.

C. Feature level fusion of finger vein and iris is executed on 120*59 of finger vein and 120*59 of iris features , After concatenation of 120*118 feature vector table and one addition column is added in 119th label column is generated for training. Ensemble machine learning classifier is used.

D. Same steps A, B and C is followed in testing phase for remaining samples, that is for 4th, 5th and 6th sample of each 40 person. But 119th column is not used because ensemble classifier will give the 119th column as predicted results.

E. Comparison of 119th column actual values with 119th predicted column will give the classification accuracy and error rate.

Same steps is carried out for 4 sample training 2 sample testing and 5 sample training and 1 sample testing.

7.2 Experimental Results

SL. NO	Biometric identifiers used	Features Used	Classification Accuracy	Error rate
1	Finger Vein	Finger Vein ULBP features	88.33%	11.67%
2	Finger Vein	Finger Vein SNBI 1:2 ULBP features	90.83%	9.17%
3	Finger Vein	Finger Vein SNBI 1:4 ULBP features	90.83%	9.17%
4	Iris	Iris ULBP features	77.5%	22.5%
5	Iris	Iris SNBI 1:2 ULBP features	80.0%	20.0%
6	Iris	Iris SNBI 1:4 ULBP features	78.33%	21.67%

Table 1: Unimodal Biometric comparison of Classification Accuracy and Error rate. Ensemble subspace discriminant classifier is used. 3 samples for training and 3 samples for testing.

SL. NO	Biometric identifiers used	Features Used for Fusion	Classifi-cation Accuracy	Error rate
1	Finger Vein & Iris	Fusion of Finger vein UBLP and Iris ULBP features	91.667%	8.33%
2	Finger Vein & Iris	Fusion of Finger vein and Iris SNBI 1:2 data sets ULBP features	92.5%	7.5%
3	Finger Vein & Iris	Fusion of Finger vein and Iris SNBI 1:4 data sets ULBP features	95.0%	5.0%

Table 2: Multimodal Biometric comparison of Classification Accuracy and Error rate. Ensemble Subspace Discriminant Classifier is used. 3 samples for training and 3 samples for testing

SL. NO	Biometric identifiers used	Features Used for Fusion	No. of Samples for Training and Testing	Classifi-cation Accuracy	Error rate
1	Finger Vein & Iris	Fusion of Finger vein and Iris SNBI 1:4 data sets ULBP features	3 samples Training, 3 samples Testing	95.0%	5.0%
2	Finger Vein & Iris	Fusion of Finger vein and Iris SNBI 1:4 data sets ULBP features	4 samples Training, 2 samples Testing	98.75%	1.25%
3	Finger Vein & Iris	Fusion of Finger vein and Iris SNBI 1:4 data sets ULBP features	5 samples Training, 1 samples Testing	100.0%	0.0%

Table 3: Multimodal Biometric comparison of Classification Accuracy and Error rate. Ensemble subspace discriminant classifier is used. Variation in training and testing samples.

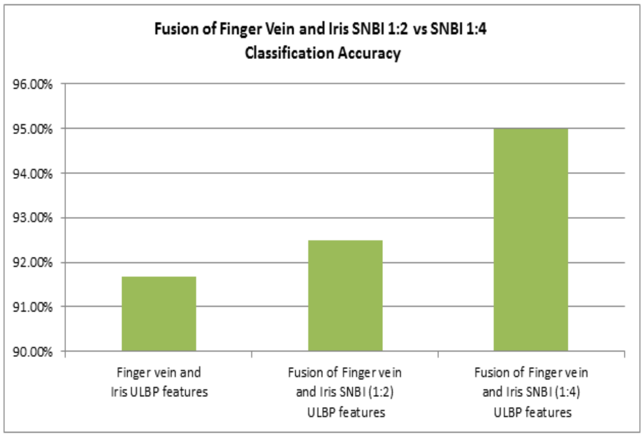

Figure 10: Classification accuracy Comparison of Unimodal Signature data sets without fusion

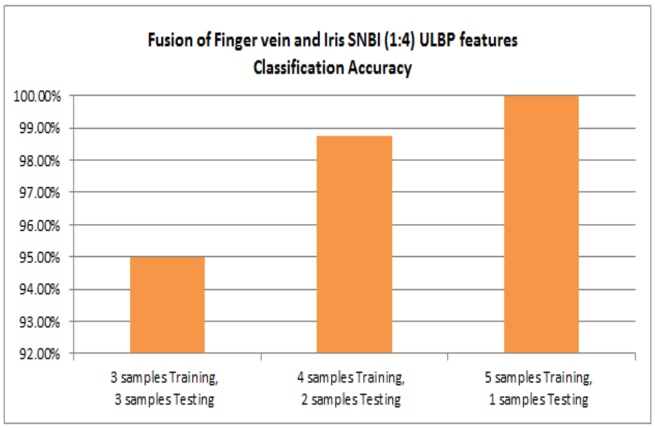

Figure 11: Classification accuracy Comparison of Multiimodal SNBI(1:4) Fusion Face data sets by varying samples count.

8. CONCLUSION

In this paper, Feature level fusion for biometric classification on both unimodal and multimodal biometrics are explored. Initially finger vein and iris samples are trained and tested with histogram features and then fusion of finger vein and iris histogram features are executed and results are plotted, from this result we can say that multimodal will give better result over unimodal data samples. Then in order to improve the multimodal recognition rate we extended our work, we applied SNBI technique to data bases so that increased resolution of data base is obtained and more rich information of features is available. SNBI technique of 1:2 ratio and 1:4 ratio is applied to both finger vein and iris data basses. Further using these data samples for fusion with various combinations better results are obtained compared to standard database. Six unimodal cases are explored in that both finger vein and iris results improved for 1:2 ratio data base. Experiment on three multimodal cases are done in which fusion of 1:4 SNBI data samples got better classification accuracy. Since we obtained better result for 1:4 SNBI data samples, we further extend our work by varying data sample count where increase in data samples for testing will drastically increase in classification accuracy.

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