Multimodal Biometric Recognition: Fusion of Modified Adaptive Bilinear Interpolation Data Samples of Face and Signature using Local Binary Pattern Features

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***Abstract*: Biometric based authentication systems use particular person characteristics which might be based on either behavior like voice, signature etc. or body structure like face, iris, palm print, fingerprint, etc. The performance of any unimodal biometric arrangement is depending on elements like surroundings, atmosphere, and sensor precision. Also, there are numerous trait unique demanding situations which include pose, expression, growing old and so forth for face reputation, occlusion and acquisition related problems for iris and terrible high-quality and social popularity related troubles for fingerprint. Hence, fusion of more than one biometric samples, traits or algorithms to achieve quality performance is another way to reap the better overall performance. In current scenario many researchers concentrating on Multimodal Biometrics with new fusion techniques ideas.**

We propose a new method of feature level fusion which uses Modified Adaptive Bilinear Interpolation (MABI) method to increase the resolution of data sample, which gives better features for fusion which gives more accurate results. In this work, experiment is done on AT&T face Cambridge University Computer Laboratory and MCYT signature Biometric Recognition Group datasets with combination of both unimodal and multimodal traits. K Nearest Neighbor (KNN) and Ensemble methods are used for classification. The proposed biometric system can be used in biometric surveillance, biometric screening for secured places, forensic applications etc.

Keywords - Biometrics; Unimodal biometric; Multimodal biometric; Local Binary Pattern (LBP), Feature Level Fusion; Modified Adaptive Bilinear Interpolation (MABI).

I. INTRODUCTION

Biometrics is continuously upgrading advanced technology which is almost used in many of the authentication and recognition identity packages. Biometric-based authentication is basically known as pattern recognition problem which makes decision based on biometric features of individuals, so that you can identify the person primarily based on specific physical or behavior tendencies, these features are utilized in biometric structures for individual authentication

. Most of the biometric systems and software's that are used in the today's world uses one biometric trait of a person or individuals those systems are mentioned as unibiometric systems.

Regardless of the sizable improvement in biometrics from the past previous years, there are nevertheless essential challenges in acquiring steady identification choice via unimodal biometric type of recognition system [1].

Biometric functions are not exactly the equal on every occasion they may be accumulated. For example, voice of a person can change because of emotional or health problem. And also, there will be no two fingerprints which are absolutely same. The fingerprint of a person degraded day by day because of physical problems like weather condition and physical activities etc. and also it may vary while capturing finger print in sensors because of improper placing of finger on sensors. Many problems of unimodal biometric systems can be solved with the aid of integrating more than one biometric tendency, like accumulating voice and face or a couple of fingerprints of the individuals etc. Those type of system's we call it as Multimodal Biometric, they are stronger in identification and recognition when compared to Unimodal, because they have multiple information's [3].

Fusion of data at different level is the crucial part of multimodal biometrics. Four degrees are available which is sensor, feature, matching, and decision stages [3]. In the proposed work, feature level fusion is used for face and signature data sets. Using feature level fusion more information is considered for Biometric traits identification and recognition. In the proposed work two Biometric samples are used that is face and signature. In first part of the feature extraction techniques for face and signature are discussed, In second sections use of bilinear interpolation to get more detailed feature is discussed and then the combination method of face and signature modalities and feature level fusion method are introduced.

II. LITERATURE SURVEY

From the year 1998 the work on multimodal biometrics is started. Since multimodal requires more than one biometric traits, face is the most common trait used to club with other biometric traits. Hong and Jain [5] where the first persons who proposed bimodal technique in the year 1998, they used

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principal component analysis and fusion techniques. Albert et.al [6] introduced automated surveillance gadget for person identification and item recognition using RGB multimodal. Then, user and item candidate regions are detected and identified the usage of strong statistical processes. The system robustly recognizes customers and updates the gadget in an online manner, figuring out and detecting new actors inside the scene.

Mamta, et al. [7] showed multimodal biometric system with face detection which covers all the face features to the search in software. Two new capabilities primarily based in this entropy are devised to cater the noticeably unsure database observed at the surveillance website. To deal with the inaccurate rankings they introduced Java utility to simulate get right of entry to a web banking website. R.Parkavi et al. Multimodal Biometrics for User Authentication fingerprint and iris biometrics are used for automated identity, trivialities and part detection strategies are used for evaluation [8]. In 2018 Waziha Kabir et al. introduced hybrid fusion for authentication [9].

From the above Literature we can justify that combination of biometric techniques and their Fusion Strategies will guaranty in improve accuracy of identification or recognition of Biometric system. And also not much work is done with the combination of face and signature biometrics, and most of the research is not done on the standard database. And fusion of MABI features are not used is multimodal biometric fusions technique.

III. DATASBASE USED FOR EXPERIMENTATION

A. Data Samples of Faces taken from: AT&T Cambridge University Computer Laboratory. In this database there are ten sample for 40 different persons. We considered all 40 different persons with 10 samples each, samples are kept in PGM format only. Same format image is used for experiment.

Fig 1: AT&T Computer Lab Face Database Sample images [11]

The images are organized in 40 directories (one for each subject), which have names of the form s1, where s1 indicates the subject number (between 1 and 40). In each of these directories, there are ten different images of that subject, which have names of the form 1.pgm, where 1 is the image number for that subject (between 1 and 10).

B. Database of offline Signatures taken from: 2004_MCYTDB_OffLineSigSubCorpus dataset, Biometric Recognition Group – ATVS MCYT dataset is of 75 users, with 15 genuine signatures and 15 Forgeries; we considered 40 users with 10 genuine signatures.

Fig 2: Different Signatures in MCYT Data Base sample signature images[13]

IV. ENHANCING RESOLUTION OF DATA SETS USING MODIFIED ADAPTIVE BILINEAR INTERPOLATION

Image interpolation occurs when you resize image from one pixel grid to another. Using bilinear interpolation technique quantity of pixels is increased for data base of face and signature images, so we can use more detailed features for fusion. Interpolation works by using known data to estimate values at unknown points.

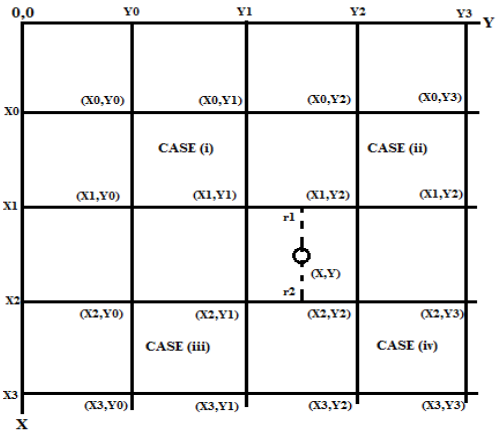

Fig. 3: Modified adaptive bilinear interpolation [12]

In normal interpolation we now that it loses photo info, and always possible of getting blurry effect. In order to overcome with the problem an improvement in interpolation is used, we used advanced change that is adaptive bilinear interpolation which increases smoothness of photograph using smoothing kernel.

The changed adaptive bilinear interpolation from a computational view point is the bilinear, where each interpolated output pixel is assigned the value computed from seven nearest pixels within the input photo. The interpolated price can have one in all feasible four outcomes [12].

They are: assume x=a, y=b

Case:1- if g (a, b) is near to g (a1, b1)

Replace g (a1, b1) with average of values at co efficient g (a0, b0), g (a0, b1), g (a1, b0) and g (a1, b1)

$$g(a1,b1) = \left(\frac{g(a0,b0) + g(a0,b1) + g(a1,b0) + g(a1,b1)}{4} \right)$$

Case:2- if g (a, b) is near to g (a1, b2)

Replace g (a1, b2) with average of values at co efficient g(a0, b2), g (a0, b3), g(a1, b2) and g (a1, b3)

$$g(a1,b2) = \left(\frac{(g(a0,b2) + g(a0,b3) + g(a1,b2) + g(a1,b3))}{4}\right)$$

Case:3- if g (a, b) is near to g (a2, b1)
Replace g (a2, b1) with average of values at co efficient g (a2, b0), g (a2, b1), g(a3, b0) and g (a3, b1)

$$g(a2\,b1) = \left(\frac{(g(a2\,b0) + g(a2\,b1) + g(a3\,b0) + g(a3\,b1))}{4}\right)$$

Case:4- if g (a, b) is near to
g (a2, b2)
Replace g (a2, b2) with average of values at co efficient

g(a2, b2), g (a2, b3), g(a3, b2) and g (a3, b3).

$$g(a2,b2) = \left(\frac{(g(a2,b2) + g(a2,b3) + g(a3,b2) + g(a3,b3))}{4}\right)$$

Then applying bilinear interpolation

$$r1 = g(a1,b1) + \left(\frac{(b - b1)}{(b2 - b1)}\right) * (g(a1,b2) - g(a1,b1))$$

$$r2 = g(a2,b1) + \left(\frac{(b - b1)}{(b2 - b1)}\right) * (g(a2,b2) - g(a2,b1))$$

$$h(a,b) = r1 + \left(\frac{(a - a1)}{(a2 - a1)}\right) * (r2 - r1)$$

Combining the bilinear interpolation results with modified adaptive bilinear interpolation to sharpen interpolated image

$$\hat{g}(a\,b) = \max(\text{result1}, \text{result2})$$

Where, result1= output of bilinear interpolation
result2= output of modified adaptive bilinear interpolation

V. FEATURE EXTRACTION METHOD

Local Binary Pattern (LBP) is an operator which uses texture features of the given sample and gives output as decimal feature vector, which is the histogram value of an input image. LBP operator considers neighbor pixels for calculation. Using threshold value, images are converted into Decimal (histogram) values. Procedure of LBP working shown in Fig4 Fig5 & Fig6.

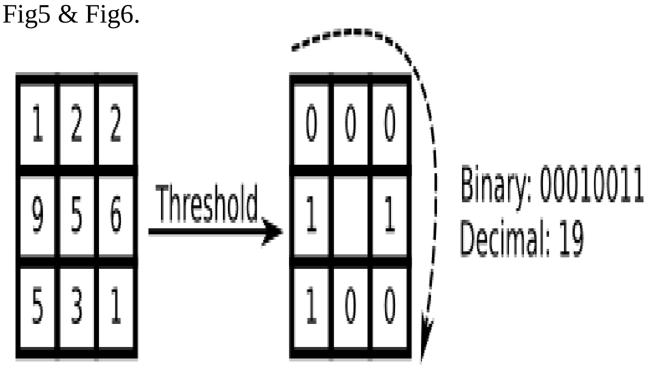

Fig 4: LBP thresholding to convert image chunks to decimal[10]

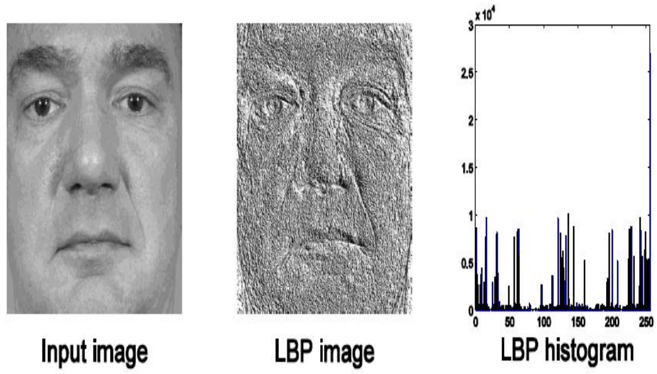

Fig5: An example of LBP image and histogram[10]

A. Feature Extraction Steps:

1. 16x16 mask is designed. This is placed over the image chunk by chunk.
2. Consider 8 neighbor pixels for each center pixel and check the threshold values either clockwise or counterclockwise shown in fig6.
3. The neighbor pixel always depends on size of the mask. Check each pixel value with center pixel, is it is > than neighbor or < neighbor and assign 1 or 0 respectively. Histogram of each chunk is calculated and finally after concatenation we will get 256-dimensional feature vector.

The value of the LBP code of a pixel (x_c, y_c) is given by:

$$LBP_{P,R} = \sum_{p=0}^{P-1} s(g_p - g_c)2^P \qquad s(x) = \begin{cases} 1, if\ x \geq 0; \\ 0, otherwise. \end{cases}$$

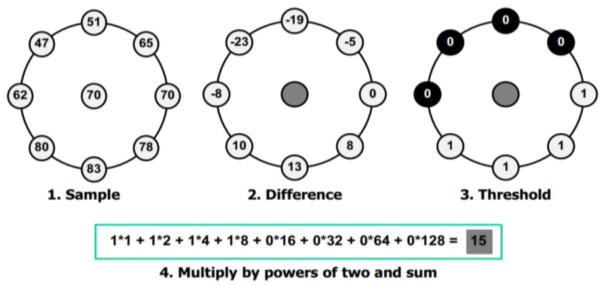

Fig 6: LBP Thresholding [10]

Using standard Local Binary Pattern features, feature length will be 256, since we working on feature fusion of multimodal biometrics; feature vector size will be longer. By using Uniform Local Binary Pattern method feature size is reduced. A beneficial extension to the LBP is referred to as uniform sample; UBLP is used in order to reduce the size of the feature vector, instead of considering all uniform neighbor pixel. Pixels with more texture information are used for designing the vector using rotation variant descriptor. We can identify uniform binary pattern by which has at most two transactions zero-one or one-zero. For example, binary pattern 0 0 0 1 0 0 0 0 (two transitions) is a uniform pattern, 0 1 0 1 0 1 0 0 (six transitions) is not a uniform pattern. LBP histogram is designed, with a separate bin for every uniform sample, and one single bin is designed for non-uniform sample. By this technique vector for a single cell reduces from 256 to fifty nine features.

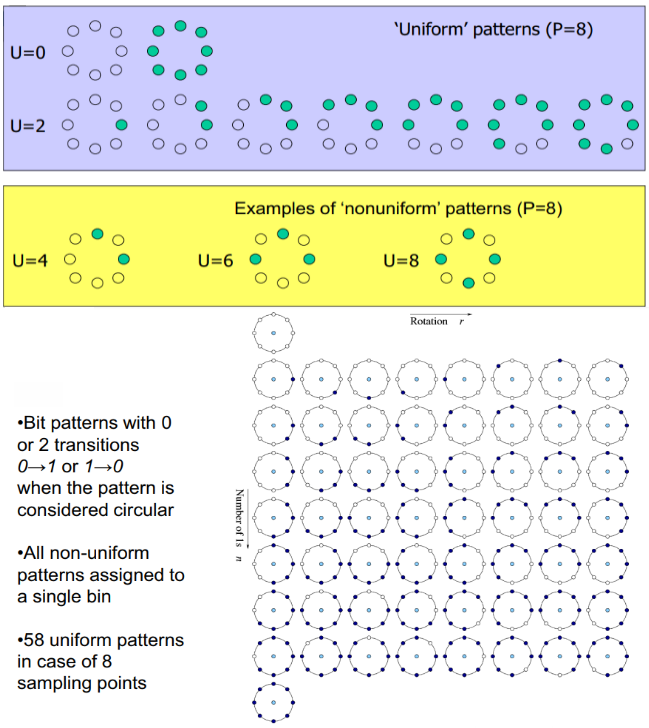

Fig 7: 58 uniform Bit patterns of LBP image[10]

The reduced 59 feature vector can now processed using machine-learning algorithm to classify images.

VI. PROPOSED ARCHITECTURE

This paper we present a new modal of feature fusion of face and signature data base shows in fig 8 and fig 9. The proposed algorithm represents the extraction of features from standard data sets and MABI datasets which is applied to enhance the quality of features, fusion technique is applied to UBLP features of MABI and standard data sets. Finally using K Nearest Neighbor (KNN) and Ensemble classifiers are used training and testing is done.

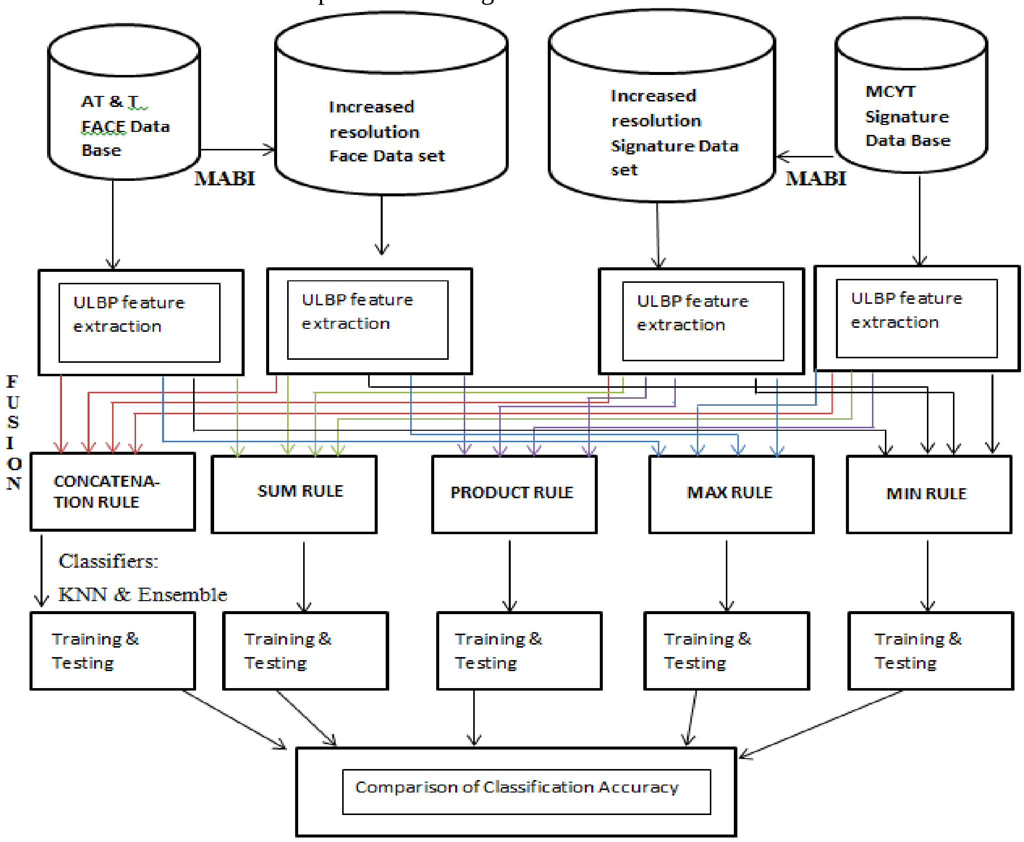

Fig 8: Proposed research work modal of feature level fusion

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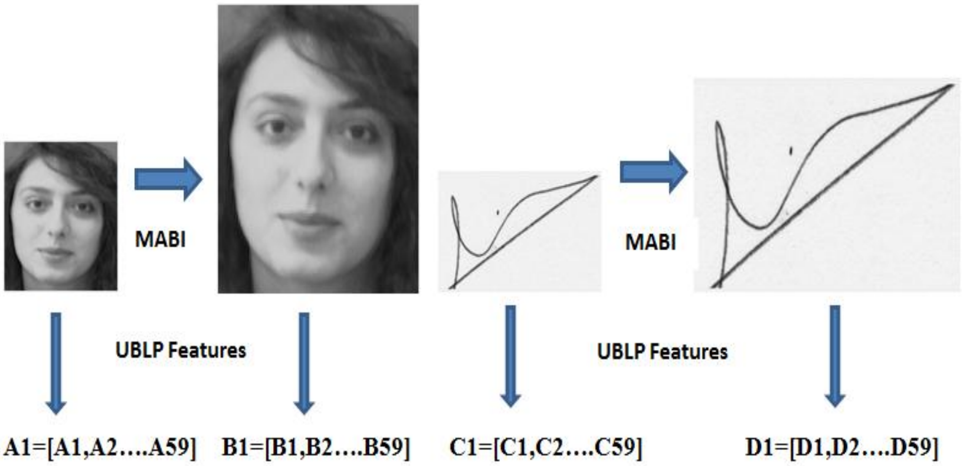

Fig 9: MABI UBLP features representation.

A. *Fusion technique for sample face & signature samples from fig9:*

1. Fusion of Unimodal UBLP Features for one sample:

Concatenation: A1= [A1, A2….A59] B1= [B1, B2….B59]
X= [A1, A2….A59, B1, B2…..B59]
X1= [A1, A2….A59, B60, B61…..B118]

Where A is feature vector of face and B is feature vector of MABI face.

2. Fusion of Multimodal UBLP Features one sample:

Concatenation: B1= [B1, B2….B59] D1= [D1, D2….D59]
Y= [B1, B2….B59, D1, D2…..D59]
Y1= [B1, B2….B59, D60, D61…..D118]

Where B is feature vector of MABI face and D is feature vector of MABI signature.

3. Fusion of Unimodal Face UBLP Features for all samples in datasets:

$$\text{Face UBLP features: } A = \begin{pmatrix} 1: A1, A2 \ldots . A59 \\ 2: A1, A2 \ldots . A59 \\ 3: A1, A2 \ldots . A59 \\ . \\ . \\ . \\ 200: A1, A2 \ldots . A59 \end{pmatrix}$$

$$\text{MABI Face UBLP features: } B = \begin{pmatrix} 1: B1, B2 \ldots . B59 \\ 2: B1, B2 \ldots . B59 \\ 3: B1, B2 \ldots . B59 \\ . \\ . \\ . \\ 200: B1, B2 \ldots . B59 \end{pmatrix}$$

Concatenation: [A B] =

$$\begin{pmatrix} 1: A1, A2 \ldots . A59\ B1, B2 \ldots . B59 \\ 2: A1, A2 \ldots . A59\ B1, B2 \ldots . B59 \\ 3: A1, A2 \ldots . A59\ B1, B2 \ldots . B59 \\ . \\ . \\ . \\ 200: A1, A2 \ldots . A59\ B1, B2 \ldots . B59 \end{pmatrix}$$

Final feature sample Face Unimodal Biometric Z =

$$\begin{pmatrix} 1: A1, A2 \ldots . A59\ B60, B61 \ldots . B118 \\ 2: A1, A2 \ldots . A59\ B60, B61 \ldots . B118 \\ 3: A1, A2 \ldots . A59\ B60, B61 \ldots . B118 \\ . \\ . \\ . \\ 200: A1, A2 \ldots . A59\ B60, B61 \ldots . B118 \end{pmatrix}$$

Where A is face feature vector and B is MABI face feature vector.

4 Fusion of Multimodal Face and Signature UBLP Features for all samples in datasets:

$$\text{MABI Face UBLP features: } B = \begin{pmatrix} 1: B1, B2 \ldots . B59 \\ 2: B1, B2 \ldots . B59 \\ 3: B1, B2 \ldots . B59 \\ . \\ . \\ . \\ 200: B1, B2 \ldots . B59 \end{pmatrix}$$

$$\text{MABI Signature UBLP features: } D = \begin{pmatrix} 1: D1, D2 \ldots . D59 \\ 2: D1, D2 \ldots . D59 \\ 3: D1, D2 \ldots . D59 \\ . \\ . \\ . \\ 200: D1, D2 \ldots . D59 \end{pmatrix}$$

Concatenation: [B D] =

$$\begin{pmatrix} 1: B1, B2 \ldots . B59\ D1, D2 \ldots . D59 \\ 2: B1, B2 \ldots . B59\ D1, D2 \ldots . D59 \\ 3: B1, B2 \ldots . B59\ D1, D2 \ldots . D59 \\ . \\ . \\ . \\ 200: B1, B2 \ldots . B59\ D1, D2 \ldots . D59 \end{pmatrix}$$

Final feature sample Face and Signature Multimodal Biometric Z =

$$\begin{pmatrix} 1: B1, B2 \ldots . B59\ D60, D61 \ldots . D118 \\ 2: B1, B2 \ldots . B59\ D60, D61 \ldots . D118 \\ 3: B1, B2 \ldots . B59\ D60, D61 \ldots . D118 \\ . \\ . \\ . \\ 200: B1, B2 \ldots . B59\ D60, D61 \ldots . D118 \end{pmatrix}$$

Where B is MABI face feature vector and D is MABI signature feature vector.

The above four cases shows the fusion of MABI UBLP feature using concatenation technique, similarly all the possibilities of SUM, Product, MIN and MAX fusion rule with all the combinations of Unimodal and Multimodal face and signature fusion shown in fig 8 is explored and results shown in the table1 and table2.

VII. CASE STUDY OF MULTIMODAL BIOMETRICS: FACE AND SIGNATURE

Using AT&T face database and MCYT signature database, Map as face 1 to signature 1 samples which belong to person1, face 2 to signature 2 samples belong to person 2. Similarly for all 40 person 10 sample each, this gives 400 multimodal samples (face and signature). Modified Adaptive Bilinear Interpolation method is applied and separate data sets created for both signature and face. Extract features from face and signature separately from 4 data sets (2 standard data sets, 2 Enhanced data sets), fusion methods like concatenate, max, min and product rule applied to face and signature features with various fusion combinations, which gives 400*119 feature vector for concatenation and 400 * 59 for max , min and product method. For Training first five samples of 40 persons that is 200*119 for concatenation and 200*199 for max, min, sum and product is input to KNN and Ensemble model, and testing remaining five samples of 40 persons.

A. Execution Steps:

Step1: Uniform Local Binary Pattern - 59 features vector extracted from each face, and stored in the matrix form. Since total 40 persons with 5 samples each is equal to 200 samples, for each sample 59 feature vector. Final feature matrix for training is 200*59.

Step2: Uniform Local Binary Pattern - 59 features vector extracted from each Signature, and stored in the matrix form. Since total 40 persons with 5 samples each is equal to 200 samples, for each sample 59 feature vector. Final feature matrix for training is 200*59.

Step3: Concatenation of face and signature vector gives 200*118 feature vector with one label name column 200*119 is trained using KNN and Ensemble classifier with 118 predictors and one response variable. Max, Min, Sum and Product of face and signature vector gives 200*59 feature vector with one label name column 200*60 is trained using KNN and Ensemble classifier with 59 predictors and one response variable.

Step 4: Features are extracted from remaining samples for testing phase, after concatenating, min, max, sum and product of face and signature features label name is not set in this case. KNN and Ensemble classifier modal will predict new label name for each feature vector.

Step 5: Comparison of Actual label name with predicted label, and classification accuracy and error rate is calculated.

VIII. EXPERIMENTAL RESULTS

Table: 1: UNIMODAL Biometric comparison of Classification Accuracy and Error rate

SL. NO	Biometric identifiers used	Features Used	Classifier	Classification Accuracy	Error rate
1	Face	Face ULBP features	KNN	78%	22%
2	Face	Face ULBP features	Ensemble	86%	14%
3	Face	Face MABI data sets ULBP features.	KNN	74.5%	25.5%
4	Face	Face MABI data sets ULBP features.	Ensemble	80.5%	19.5%
5	Signature	Signature ULBP features	KNN	53%	47%
6	Signature	Signature ULBP features	Ensemble	67%	33%
7	Signature	Signature MABI data sets ULBP features.	KNN	40%	60%
8	Signature	Signature MABI data sets ULBP features.	Ensemble	83.5%	16.5%

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Table: 2: MULTIMODAL Biometric comparison of Classification Accuracy and Error rate

SL. NO	Biometric identifiers used	Features Used for Fusion	Feature Fusion method	Classifier	Classifi-cation Accuracy	Error rate
1	Face & MABI Face	Fusion of Face UBLP and MABI data sets ULBP features	Fusion (Concatenation)	KNN	88%	12%
2	Face & MABI Face	Fusion of Face UBLP and MABI data sets ULBP features	Fusion (Sum rule)	KNN	75%	25%
3	Face & MABI Face	Fusion of Face UBLP and MABI data sets ULBP features	Fusion (Product rule)	KNN	79.5%	20.5%
4	Face & MABI Face	Fusion of Face UBLP and MABI data sets ULBP features	Fusion (Max rule)	KNN	73%	27%
5	Face & MABI Face	Fusion of Face UBLP and MABI data sets ULBP features	Fusion (Min rule)	KNN	77.5%	22.5%
6	Face & MABI Face	Fusion of Face UBLP and MABI data sets ULBP features	Fusion (Concatenation)	Ensemble	94.5%	5.5%
7	Face & MABI Face	Fusion of Face UBLP and MABI data sets ULBP features	Fusion (Sum rule)	Ensemble	76.5%	23.5%
8	Face & MABI Face	Fusion of Face UBLP and MABI data sets ULBP features	Fusion (Product rule)	Ensemble	78.5%	21.5%
9	Face & MABI Face	Fusion of Face UBLP and MABI data sets ULBP features	Fusion (Max rule)	Ensemble	76%	24%
10	Face & MABI Face	Fusion of Face UBLP and MABI data sets ULBP features	Fusion (Min rule)	Ensemble	79%	21%
11	Signature & MABI Signature	Fusion of Signature UBLP and MABI data sets ULBP features	Fusion (Concatenation)	KNN	56%	44%

SL. NO	Biometric identifiers used	Features Used for Fusion	Feature Fusion method	Classifier	Classifi-cation Accuracy	Error rate
12	Signature & MABI Signature	Fusion of Signature UBLP and MABI data sets ULBP features	Fusion (Sum rule)	KNN	34.5%	65.5%
13	Signature & MABI Signature	Fusion of Signature UBLP and MABI data sets ULBP features	Fusion (Product rule)	KNN	38%	62%
14	Signature & MABI Signature	Fusion of Signature UBLP and MABI data sets ULBP features	Fusion (Max rule)	KNN	34%	66%
15	Signature & MABI Signature	Fusion of Signature UBLP and MABI data sets ULBP features	Fusion (Min rule)	KNN	39%	61%
16	Signature & MABI Signature	Fusion of Signature UBLP and MABI data sets ULBP features	Fusion (Concatenation)	Ensemble	91%	9%
17	Signature & MABI Signature	Fusion of Signature UBLP and MABI data sets ULBP features	Fusion (Sum rule)	Ensemble	81.5%	18.5%
18	Signature & MABI Signature	Fusion of Signature UBLP and MABI data sets ULBP features	Fusion (Product rule)	Ensemble	77.5%	22.5%
19	Signature & MABI Signature	Fusion of Signature UBLP and MABI data sets ULBP features	Fusion (Max rule)	Ensemble	83.5%	16.5%
20	Signature & MABI Signature	Fusion of Signature UBLP and MABI data sets ULBP features	Fusion (Min rule)	Ensemble	78%	22%
21	Face & Signature	Fusion of Face and signature data sets ULBP features	Fusion (Concatenation)	KNN	84.5%	15.5%
22	Face & Signature	Fusion of Face and signature data sets ULBP features	Fusion (Sum rule)	KNN	79%	21%
23	Face & Signature	Fusion of Face and signature data sets ULBP features	Fusion (Product rule)	KNN	71%	29%
24	Face & Signature	Fusion of Face and signature data sets ULBP features	Fusion (Max rule)	KNN	83.5%	16.5%
25	Face & Signature	Fusion of Face and signature data sets ULBP features	Fusion (Min rule)	KNN	57%	43%
26	Face & Signature	Fusion of Face and signature data sets ULBP features	Fusion (Concatenation)	Ensemble	92.5%	7.5%
27	Face & Signature	Fusion of Face and signature data sets ULBP features	Fusion (Sum rule)	Ensemble	89%	11%
28	Face & Signature	Fusion of Face and signature data sets ULBP features	Fusion (Product rule)	Ensemble	84.5%	15.5%
29	Face & Signature	Fusion of Face and signature data sets ULBP features	Fusion (Max rule)	Ensemble	88%	12%
30	Face & Signature	Fusion of Face and signature data sets ULBP features	Fusion (Min rule)	Ensemble	83.5%	16.5%
31	Face & Signature	Fusion of Face MABI and Signature MABI data sets ULBP features	Fusion (Concatenation)	KNN	74.5%	25.5%

SL. NO	Biometric identifiers used	Features Used for Fusion	Feature Fusion method	Classifier	Classifi-cation Accuracy	Error rate
32	Face & Signature	Fusion of Face MABI and Signature MABI data sets ULBP features	Fusion (Sum rule)	KNN	71.5%	28.5%
33	Face & Signature	Fusion of Face MABI and Signature MABI data sets ULBP features	Fusion (Product rule)	KNN	66.5%	33.5%
34	Face & Signature	Fusion of Face MABI and Signature MABI data sets ULBP features	Fusion (Max rule)	KNN	78%	22%
35	Face & Signature	Fusion of Face MABI and Signature MABI d ta sets ULBP features	Fusion (Min rule)	KNN	58.5%	41.5%
36	Face & Signature	Fusion of Face MABI and Signature MABI data sets ULBP features	Fusion (Concatenation)	Ensemble	93.5%	6.5%
37	Face & Signature	Fusion of Face MABI and Signature MABI data sets ULBP features	Fusion (Sum rule)	Ensemble	80%	20%
38	Face & Signature	Fusion of Face MABI and Signature MABI data sets ULBP features	Fusion (Product rule)	Ensemble	78.5%	21.5%
39	Face & Signature	Fusion of Face MABI and Signature MABI data sets ULBP features	Fusion (Max rule)	Ensemble	83.5%	16.5%
40	Face & Signature	Fusion of Face MABI and Signature MABI data sets ULBP features	Fusion (Min rule)	Ensemble	84%	16%

IX. CONCLUSION

In this paper, biometrics classification for unimodal and multimodal biometrics are done using various feature level fusion. At first stage without fusion, experiment is tested on face and signature data sets using ULBP features and then fusion of face and signature data sets are explored using various fusion techniques and results are plotted. At the second stage using MABI technique state of art fusion of increased resolution features with UBLP features tested and examined.

In Unimodal biometric Signature recognition rate is considerably improved by 16.5% classification accuracy by using MABI features for Ensemble classifier. Multimodal biometrics classification with MABI face and MABI signature features gave better results compared to standard features. 8 unimodal and 40 multimodal case study models are developed and tested. From the case study we can see that biometric recognition rate will be increased by using Multimodal feature fusion, In proposed work using fusion of MABI UBLP features of Face and Signature classification accuracy is increased to 93.5%. Even though LBP is used for texture variation Biometric traits, we used LBP for signature samples with MABI technique which increased overall results of signature identification.

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