# Feature and Decision Level Fusion in Children Multimodal Biometrics

**Bhavya D. N., Chethan H. K.**

***Abstract:** In this paper, we design method for recognition of fingerprint and IRIS using feature level fusion and decision level fusion in Children multimodal biometric system. Initially, Histogram of Gradients (HOG), Gabour and Maximum filter response are extracted from both the domains of fingerprint and IRIS and considered for identification accuracy. The combination of feature vector of all the possible features is recommended by biometrics traits of fusion. For fusion vector the Principal Component Analysis (PCA) is used to select features. The reduced features are fed into fusion classifier of K-Nearest Neighbor (KNN), Support Vector Machine (SVM), Navie Bayes(NB). For children multimodal biometric system the suitable combination of features and fusion classifiers is identified. The experimentation conducted on children's fingerprint and IRIS database and results reveal that fusion combination outperforms individual. In addition the proposed model advances the unimodal biometrics system.***

***Keywords:** Gabor, MR filter, HOG, KNN,SVM,NB*

## I. INTRODUCTION

Biometric systems have emerged as a new solution to satisfy our society's ever increasing demand of improved security requirements. The biometric system recognizes an individual based on an individual's own physiological and/or behavioral characteristics [1-3]. In literature, these features are also referred as traits. The physiological characteristics include fingerprint, palm print, iris, hand geometry, inner knuckle print (IKP), face, ear, etc., while voice, signature, gait, keystrokes are behavioural features etc. The major advantage of utilizing biometric traits are, it is difficult for intruders to steal biometric traits and physical presence of an individual is essential at the time of providing information for the recognition process. Furthermore, it offers reliable solutions to develop automated or semi-automated approaches to recognize individuals.

Multi-biometric system is success because of fusion scheme. The fusion scheme combines information from various different biometrics source. The biometric system will reduced the information at each level to process the information. Here the final decision will contain abstract level of information. The four important modules are Sensor module, Feature extraction module, Matching module and Decision-making module are used fused at different level of different biometric traits. Later the feature level fusion and decision level fusion are employed. In our work the literature survey is presented in section 2. In section 3 discussion of feature extraction. The feature reduction is presented in section 4. The process of classifier is discussed in section 5. Final section 6 presents the result discussion. Results shows that fusion strategies increase the performance of biometric system.

Multiple sensors or multiple snapshots is used obtained the Raw data using of a single biometric trait captured using only one sensor [5-6] can be used for performing sensor level fusion. Fusion of raw biometric data depends on the sensors used for capturing biometric data. Very few reports were found in literature related to sensor level fusion. Features derived from preprocessed images are integrated for performing feature level fusion [7-12]. Lakshmi Deepika et al. [13] have discussed a multi algorithmic approach to extract features from hand veins. Extracted features are concatenated to create a single feature vector. FAR of 0.3% and FRR of 0.54% for a database consisting of images from 74 individuals are reported. Yong-Fang Yao et al. [14] have proposed a weighing strategy for a multimodal system that utilizes face and palm print modalities. The recognition rate of 90.7% is reported in the experimental test made with face and palm print data set. Jian-Gang Wang et al. [15] have presented an acquisition setup that acquires the palm print and palm vein images of an individual using two cameras. A new feature called as "junction" derived from both the palm print and palm vein image is proposed. Experimental results indicate a low error rate in multimodal palm print and palm vein than that of either palm print or palm vein individually. Nageshkumar et al. [16] have proposed a multimodal biometric system based on face and palm print. A feature level fusion strategy based on Eigen values and Eigen vectors is proposed. Experiments conducted on 720 images acquired from 120 individuals report a FAR of 2.4% and FRR of 0.8%. Feature level fusion produces best results when modalities are related (e.g. Iris left and right eye) than when they are unrelated (e.g., hand and face). Finding the relationship between features is difficult when different algorithms are used to extract features from different traits. Also concatenation of feature vectors results in a feature vector with high dimensionality, which leads to higher computational load. The match scores output by multiple biometric matchers are combined to generate a single scalar score. Miguel A et al. [17] proposed a multimodal system based on the hand geometry, palm print and finger print modalities. Different set of rules for feature, score and decision level fusion are proposed.

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Experiments conducted report best results for decision level fusion with FAR of 0% and FRR of 0.15%. A database of 109 user images is used for experimentation. Jingyan Wang et al. [18] have presented a new fusion scheme to fuse iris and palm print modalities at score level. An error rate of 1.50% is reported with their work highlighting the effect of score normalization on computational time required for the entire recognition process. Yang et al. [19] have proposed two recognition models based on fingerprint, palm print and hand geometry. In the first model the match score from finger prints of all fingers are fused and the resultant score is fused with palm-print and hand-geometry scores. In the second model palm print and fingerprint scores are fused first and the resulting matching score is fused with the hand geometry match score. Results presented highlight the advantages of using fusion schemes at match score level in multimodal recognition systems. Other score level fusion schemes proposed in the literature are reported in [20-22]. Monawar et al. [23] have proposed a markov chain method for consolidating the rank information of face, iris and ear modality matchers. Rank(1) CIP of 98.5% is reported for markov chain method. Monawar et al. [24] have consolidated rank information of face, ear and signature matchers using logistic regression and Borda count methods. Authors have modified both the methods by considering the top ranks identities that appear in two rank lists out of three rank lists of face, ear and signature matchers. Abass et al. [25] have incorporated image quality information in the fusion rule to analyse the performance of rank-level fusion for logistic regression and Borda count method. Quality based scheme is proposed by the authors to evaluate the rank level performance for varying image quality in input data. For logistic regression method rank 1 CIP percentage decreases if the quality of input image changes from the quality of images used in the training phase. Stable Rank(1) CIP of 94% is reported for a borda count method for varying image quality. Rank list obtained from three different palmprint matchers that uses Line, Gabor and Eigen palm features are consolidated using a non linear rank level fusion approach by Ajay Kumar et al. [26]. The authors have investigated Borda count, weighted Borda count, highest & product of ranks and Bucklin majority voting methods. Results presented suggest that rank level combination achieves higher Rank(1) CIP. Authors have reported 84% Rank(1) CIP for Borda count and average Rank(1) CIP of 98.75% for the non linear rank level fusion methods. A multimodal biometric system using face and ear biometric traits with fusion applied at rank level is proposed by Padma Polash Paul and Marina Gavrilova[27]. Multiple random projections are used to generate multiple templates and rank level fusion is applied to generate consolidated decision from multiple ranks. Authors have reported 64% and 70% Rank(1) CIP for face and ear traits. Rank(1) CIP of 84% is reported for the multiple template approach. A predictor based technique that uses rank and score information of unimodal traits to improve the performance of biometric system is proposed by Emanuela Marasco et al. [28]. Information generated by unimodal trait predictors is used to design rank level fusion scheme that can work in a multimodal scenario. CIP of 97.22% is reported, but predictors are developed using the training phase data. Match score level fusion approaches are applied to verification and rank level fusion methods for identification functionality of the biometric system. These approaches are widely used because the score output from matching modules can be easily integrated. Decision level fusion presented in the literature includes weighted combination [29], AND and OR rules [30], majority voting [31] and Bayesian decision fusion [32]. Decision level fusion is less preferred since the information content available from individual decision modules is either true or false.

Bharadwaj et al. [33] and Jain et al. [34] proposed the biometric recognition using face and fingerprint. Bharadwaj et al. [33] proposed a system for face recognition. The children's finger print data is collected and presented by Jain et al. [34]. Bharadwaj et al. [33] have created a face database of 1200 images for newchildrens. Jain et al. [34] created a database of children of age 0 to 5 years. Tiwari et al. [35] presents multimodal biometrics system for new born children's consists of face, ear and headprint. Main drawback of this research is availability of young children database.

## II. METHODLOGY

Here, we planned a Children multimodal biometric system of fingerprint and IRIS by integrating the information at feature level and decision level. Initially, HOG, Maximum Response Filter and Gabor features are extracted from both fingerprint and IRIS of a Children and are individually studied for their identification accuracies. Later, the fusion of the biometric traits is recommended at feature level using the best representation, which is subsequently classified using fusion classifier of NB, SVM and KNN.

### A. Feature Extraction

In proposed system, for given images we extracted Gabor Filter responses, HOG and MR filter features.

### B. Histogram of Oriented Gradients (HOG)

Histogram of oriented gradients (HOG)[37] is a descriptor usedto detect the objects in image. This technique computes the occurrence of incline orientation in all the localized portion of an image. The HOG descriptors are defined by the appearance of the object and represented by intensity gradients distribution or the edge direction. In this algorithm every picture is represented with cells and for each cell the histogram is computed. This histograms are called as Descriptor. The neighborhood histograms can be differentiate standardized and precision can be enhanced by computing a measure of the force for a bigger district of the question is

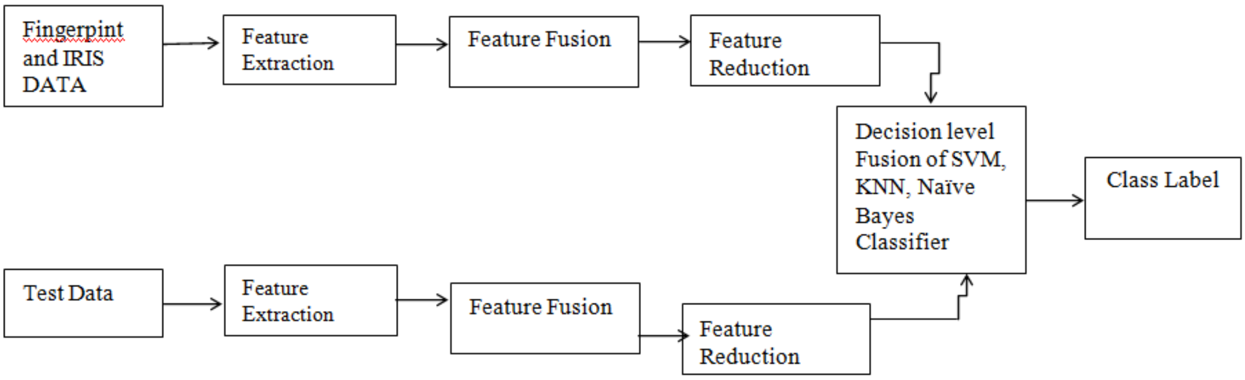


**Figure 1: Shows the Block Daigram of Proposed method**

know as piece, and utilizing the square esteem is utilized standardize all cells inside this piece. The HOG descriptors is a window base descriptor it is commonly used in object recognition and human detecting method it will compute that local to a detected interest point. Window is entree upon the point of interest and divides into regular square grids (n x n). Within the reach an every cell the grids a frequency histogram is computed representing the distribution of edges orientation within in these cells. The limited intensity gradients or boundary detection distribution distinguishes the appearance of the local object and shape. In octal region to HOG features are intended by taking edge intensity of oriented histogram. In HOG features extraction process, the feature extraction is complete form a local region with 16 x 16 pixels. The 8 orientations Histogram of Gradients are calculated from of 4 x 4 cells and hence total num of HOG features comes 128 =8 x(4 x 4) which is done from 16 x 16 local regions.

The descriptor with a small change in the positions of the window and gives the low prominence to gradients in order to avoid the sudden changes than of far from centres of descriptor. The weight to each magnitude pixel is assigned by Gaussian weighing function σ which is equal to 1 half of the size of the descriptor window. A HOG features describes the narrow shape of objects, having edge information at different cells. In plain reigns, the histogram of oriented gradients[37] will have flatter dimensions for example: ground or building wall whereas in the borders, most one of the elements in the histogram has a largest value and it indicates edge direction. Even though the images are normalize to the place and scale, the positing of main features will not be registered with the same position in the grid. The HOG features are resilient of photometric transformations and local geometry. Translation or orations of the object with much smaller neighboring spatial bin size has comparatively small effect.

## C. Maximum Response Filter

MR works the rule of nuclear attractive reverberation, to delineate spatial areas and dissect its cores and proton properties in view of its collaborations and core turns. As we as a whole know human firm is comprised of water and fat atoms. Each water atoms contain 2 hydrogen particles. Every hydrogen atoms contain a few protons and a core. These protons are dissected for neurotic and mental parts of tissues. At the point when hydrogen particle is set in attractive field, its cores adjust itself in course opposite to its field connected. At the point when attractive field is expelled, cores realign itself at typical position. This create RF motion at reverberation recurrence. Recurrence and stage information of these signs are gathered in k-space. In parallel imaging, there are different curls are utilized for parallel execution of numerous MR pictures. Recurrence and stage factor prompted utilization of aggregate of-square calculation. It is characterized as the quadrangle foundation of aggregate of square of pixel from singular loop. With its assistance, unmistakable data can be acquired by examining distinctive k-space parallely and diminishes its securing time. The quantity of k-space diagram is lessened. Each picture that is acquired from recipient is a sub inspected pictures.

So picture get from each curl is associated picture. These pictures are unfurl or missed k-space lines are recovered utilizing earlier data. Parallel reproduction techniques are isolated into two. Picture territory based modernization and k-space based strategy. In first technique, picture is unfurled utilizing loop maps. In second, miss k-space lines are recovered to remake a picture. Its primary favorable position is its securing speed that expels bending caused by specific curios, by averaging them[38].

## D. Gabor Filter Responses

Gabor functions belong to frequency-based approaches. In this approach, texture is an image pattern containing a repetitive structure that's categorized in a Fourier domain. The challenge is to deal with trade-off between joint uncertainty and frequency domains. The aim of the gabor function minimize the joint uncertainty in space and frequency. The gabor filter are applied on bank of scale and orientation selective to an image[39]. Gabor function g(x; y) and its Fourier transform G (u; v) is define by

$$g(x,y)=\left(\frac{1}{2\pi\sigma_x\sigma_y}\right)\exp\left[-\frac{1}{2}\left(\frac{x^2}{\sigma_x{}^2}+\frac{y^2}{\sigma_y{}^2}\right)+2\pi iWx\right]$$

and

$$G(u,v)=\exp\left\{-\frac{1}{2}\left[\frac{(u-W)^2}{\sigma_u{}^2}+\frac{v^2}{\sigma_v{}^2}\right]\right\}$$

where $i=\sqrt{-1}$ , $\sigma_u = 1/2\pi\sigma_x$ and $\sigma_v = 1/2\pi\sigma_y$ control the tradeoff between spatial and frequency resolution, and W controls the modulation.


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## III. PRINCIPAL COMPONENT ANALYSIS (PCA)

Principal Component Analysis (PCA) is a current approach for reducing the dimension of feature vectors and analyzing data proposed by Jolliffe et al. [40].
PCA Algorithm is as follows:

Normalization of features to zero means and unit variances.
Calculation of covariance matrix C.
Finding Eigen values and the corresponding Eigen vectors.
Sorting the Eigen values from highest to lowest.

Here Eigen values with Greater Values is the first principal component that contains important information

Reject low Eigen value principal components.

## IV. DECISION LEVEL FUSION

The extracted features are fed into fusion classifier of KNN, SVM and Naïve bayes. Here we combine the decision of all the classifiers.

### A. K Nearest Neighbor (KNN)

New instance query is classified in K-nearest neighbour classifier[41] based majority voting. It also a supervised learning algorithm. The aim of the algorithm to classify the new object based on features and per defined training samples. The training samples are defined by n-dimensional numeric features. Every sample is a point in dimensional space. Most challenging is to search the K value. If K>1 then majority vote decide the class label. The KNN algorithm deals with various data types like ordinal, nominal to quantitative scale. The algorithm uses multiple features Si to classify the object R. The Euclidean distance between Query sample and all the training samples are computed. Later the distance values are sorted from lowest to highest. Later class labels are assigned for the sorted distance. Finally majority voting on class label is obtained. Test sample is assigned to particular class.

### B. Naive Bayes classifier

The new sample is classified to probable class using Naïve Bayes classifier[42]. Here for the given class value the features are independent conditionally. When compare to other classification method Naïve bayes classifier performs best and classify the new object to correct class.
Algorithm follows two steps. Training step: in which parameter of probability distribution is estimated and features are independent conditionally. Secondly the predication step here posterior probability of test sample is computed for sample belong each class. The test sample is assigned to particular class based on posterior probability.
Bayes theorem uses the eqn as given in eq.

$$P(C_i|V) = \frac{P(V|C_i)P(C_i)}{P(V)}$$

Naïve assumption of class conditional independence Thus,

$$P(V|C_i) = \prod_{k=1}^{n} P(x_k|C_i)$$

### C. Support vector machine

SVM [44,45] is one of successful tool to classify the data introduced by Vapnik, 1998. Initially it a binary classifier, aim is to find hyper plane to classify the two groups data. In addition, it acts has liner classifier in high dimensional space. The non-linear classifier archives good accuracy by by exploiting the boundary between the classes. The primal optimization problem is solved using SVM with L1 soft-margin formulation

$$\min \frac{1}{2}\|w\|^2 + c\sum_{ij=1}^{w} \xi_1$$
$$sty_i(w.z_i + b) \geq 1\xi_1 \xi \geq 0.i = 1.2......m$$

C is a regularization parameter.

## V. EXPERIMENTAL SETUP

Fingerprint and IRIS based Children Multimodal biometrics are considered. For both databases the features like Gabour, MR filter, HOG are extracted. Feature selection is through PCA. Classification is through kNN, Naive Bayes and SVM Classifier.

### A. Results

Here, we described the experimental results obtained for the proposed multimodal biometric system based on feature level fusion of FingerPrint and IRIS. The proposed model is tested on database of iris, fingerprint, and face images of Children Multimodal Biometric Database (CMBD). That Contains 100 children with age grauop of 18 months to 4 years, acquired over two sessions[36]. In order to evaluate the performance of the proposed classification system, Gabor and MRfilter, HOG features are extracted from both databases. The system was trained using 70%, 50%, and 30% samples per user and was tested with the remaining samples per user respectively.

Figure 2 shows the accuracy of the summary of the individual and fusion classifier recognition accuracy under varying database size using different representatives. Further we also conducted experimentation by varying by selecting the features using PCA shown in Table 1. Table 1 shows the results of individual and fusion classifier. From accuracy tables it is observed that the feature level fusion of fingerprint and IRIS and fusion of various classifiers outperforms the fingerprint and IRIS when they are considered individually. Hence this fused feature vector is recommended for the proposed Children multimodal biometric system.

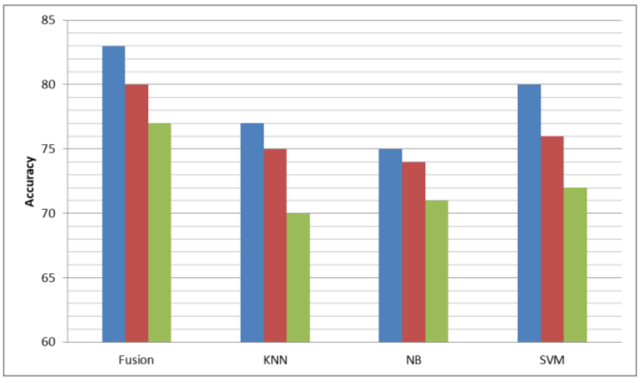


**Figure 2: shows the accuracy of Individual and fusion classifier**

**Table 1: shows results of recognition rates under varying PCA features**

| PCA based features | Recognition rate | | | |
|---|---|---|---|---|
| | K-NN | Naïve Bayes | SVM | Fusion |
| 20 | 84 | 85.8 | 83.2 | 86.1 |
| 40 | 86.1 | 86.2 | 88 | 88 |
| 60 | 88.2 | 88.1 | 91 | 91.2 |
| 80 | 88.6 | 90.4 | 92.2 | 93 |
| 100 | 89 | 90.8 | 93 | 93 |
| 120 | 89 | 91 | 93 | 93 |
| 140 | 89 | 91 | 93.4 | 94 |

## VI. CONCLUSION

The two biometrics traits like fingerprint and IRIS are mostly used applications. The fusion of both traits is presented in this work. Some of the advantages of biometrics are robustness to noise, lowcost, off-the-shelf hardware data acquisition. In this work, we presented Multimodal System by fusing various features and classifiers. For fusion features we have used MR filter, HOG and Gabor. The features are fed into fusion classifier of KNN, SVM and NB. The experimentation is conducted on Children Multimodal Biometric Database (CMBD). The experimental results show that fusion information from independent source increase the performance. This work does investigation at feature level and decision level and the results are motivating.

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