

## Analysis of Dimensionality Reduction Techniques on IRIS Code

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### ABSTRACT

IRIS is considered as one of the best biometric model for representing a human Identity. An efficient IRIS recognition technique with reduced space complexity is one of the challenging aspects in IRIS recognition. In this paper we improve the recognition accuracy and efficiency using the IRIS code obtained through Daugman's technique and then Dimensionality Reduction is applied. IRIS of a test is recognized by using minimum hamming distance from trained IRIS codes. MLE (Maximum Likelihood Estimation) technique is used to determine the significant and predominant features as each Gabor coefficient does not have same weight in generating a unique pattern for each IRIS. Further, features are reduced by using PCA (Principal Component Analysis) and mapped to a low dimensional feature space using SOM (Self Organizing Map). Experimental results show that efficiency of the system is 100% for 50 classes and 99.73% for 500 classes which is better than the other techniques proposed so far in this direction. Results also show that the recognition time has been found reduced (3.6 seconds for 1500 classes) which is also better than SVM (Support Vector Machine) based technique.

*Keywords* - IRIS, IRIS code, SOM, Dimensionality Reduction, PCA, Hamming Distance, Gabor filter, MLE.

### I. INTRODUCTION

A person's iris can be matched from a set of binarized iris representation using hamming distance and with the help of any appropriate search technique [1]. When the search is adopted in the non binary domain with the help of existing features using a kernel based technique then the matching complexity increases as number of classes increase[3]. Kernel based classifiers are best suited for iris recognition in non binary domain [2] and it is important to ensure that kernels complexity is to be reduced. In this paper we propose a dimensionality reduction technique for decreasing the number of dimensions of feature vectors. In this work we use PCA based dimensionality reduction over the IRIS code suggested by Daugman to show that the accuracy and speed of the technique increases with dimensionality reduction.

### II. PROBLEM FORMATION

The probability of false acceptance is  $1/10^{31}$  for a 2048 bit IRIS code[1]. If confidence term in Hamming distance is considered to be 0.321[1], the false acceptance and rejection rates are almost equi-probable. IRIS code is a binary encoding of the Gabor coefficients obtained after IRIS segmentation. If the coefficients are considered as features then SVM based classifier can achieve accuracy in recognition as high as 99.54%[5]. Further assigning equal weight to all bits of IRIS code has several limitations since all bits cannot equally represent a person's identity. Most of the recent IRIS research is organized in the direction of identifying the most dominant features from segmented IRIS part and classifying them using a kernel based classifier, predominantly a SVM classifier. As kernel based classifiers are basically 2 class classifiers, with increase in number of classes the complexity of classification increases [6]. Hence extracting dominant patterns from the Gabor coefficients and generating the IRIS code from this pattern is optimum, but different persons may have different dominant patterns resulting in variable length IRIS code. Daugman[1] in his discussion about commensurability of IRIS codes has proven that variable length IRIS codes cannot be matched with any accepted confidence. Therefore the problem of generating equi-length IRIS code from dominating feature set remains unsolved.

### III. PROPOSED SYSTEM

IRIS is segmented and Gabor Coefficients are extracted by using Daugman's technique [1]. The features from all the trained classes and instances were first saved in the database without generating the IRIS code. MLE estimates the intrinsic dimensionality present within the dataset which is used by PCA to reduce the dataset to low dimensional feature space which is further scaled down to 2D feature space using SOM. Therefore high dimensional features are mapped to a two dimensional lattice feature space using SOM so that features from any two IRIS can be compared just by Euclidian distance in 2-D feature plane. If we consider a matrix of size 100 x 100 to represent SOM plane then any IRIS instance can be represented just by ones and zeros, where a '1' will appear at each position that an instance of the IRIS class is appearing in the feature plane and 0 elsewhere. Thus any given IRIS features once mapped

to SOM plane can be recognized as the class that has maximum correlated 1's with the test features. The block diagram of the proposed system is shown in figure 1.

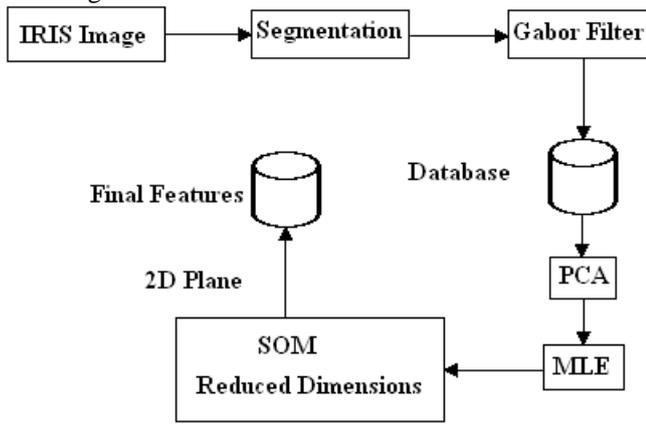


Figure 1. Block Diagram of the proposed system.

#### IV. METHODOLOGY

First IRIS image is preprocessed and segmented using the technique proposed by Daugman[1]. The extracted features are complex with imaginary part being non zero and the real part containing some zero DC offset. Entire complex output of the features extraction process is considered as the feature vectors. We have shown that the feature normalization is one of the most important aspects for dimensionality reduction[12]. Therefore the obtained features need to be normalized before processing with PCA. For the normalization process the maximum of the real part of the feature space is obtained and entire value set is divided by the same. Intrinsic dimension 'd' ( $d < D$ , where  $D$  is the actual dimensionality of the feature space) is calculated using MLE. 'd' and Normalized feature vectors are used to compute the mapping in the low dimensional plane using PCA. There are two immediate choices for reducing the dimensions of the Feature vectors of IRIS dataset. Dimensionality reduction achieved from PCA can be used directly as final feature vectors or SOM can also be used directly without using PCA. As SOM does not take intrinsic dimensionality into consideration and applies data set reduction to 2-d, reducing raw data by SOM is inefficient which can also be seen from figure 4, which shows that the performance of the system is unacceptably low if SOM is used directly over the actual feature vectors. On the other hand, resulting reduced data set from PCA can also be used for IRIS recognition, but the figure 5 proves that comparing complex features is more time consuming than the binary comparison proposed here. Ideally a  $10 \times 10$  lattice is enough to represent 100 classes. But not all classes will be present at a unique cell in the lattice. Hence we experimented by changing number of classes and observed the accuracy. Experiments with CASIA database shows that for  $N$  classes  $P \times P$

cell structure is most suitable, where  $2^P \geq 2 \times N$ . Also it is observed that the results are better if  $P$  is represented as 2's degree. Therefore  $2^x = P$ , can be considered as an ideal solution for better match. Hence for a 10,000 class problem,  $128 \times 128$  lattice structure is sufficient.  $512 \times 512$  structure can represent up to 131072 classes. Further experiments were conducted with more number of instances of a class. It is seen that four training instance leads to almost 100% accuracy irrespective of the number of classes.

IRIS recognition problem can be thought of as either a template matching problem or a classification problem. Like other biometric solutions, template matching is widely acceptable and used in IRIS recognition problem. But as we have discussed in problem formation section, template matching technique has its own limitation as it allocates equal weight to each feature.

In the proposed work we handle IRIS recognition as a classification problem. Rather than extracting binary templates from the features of IRIS images, we deal with the features and classify the features using support vector machine. The method is elaborated in short:

First IRIS image is preprocessed and segmented using the technique proposed by Daugman[1]. It extracts the IRIS part from the rest of the eye image. Once IRIS part is extracted, it is converted to a fixed size image of size  $80 \times 80$ . Two -Dimensional Gabor filter is applied to segmented IRIS image. The resulting image projections of 2-D Gabor filters are complex in nature where the imaginary part does not possess any DC response. The real part is adjusted to produce non DC component. However, as the complex feature itself is considered in the proposed work, the feature even without adjustment of the real part would have no DC component, which is an important task in feature matching process.

One of the feasible ways of recognizing a test IRIS image will be to extract the features of the test image and classify such features with that of the features of the images stored in the database using any suitable classifier like ANN, SVM, KNN etc., but the complexity of the classifier increases significantly with the increase of the classes. This is attributed by optimization problem where huge numbers of features and classes makes it computationally difficult for the classifier to classify the features in minimum time with maximum accuracy. Therefore we propose a dimensionality reduction of the feature vectors. Normally dimension reductionality is considered as a visualization problem where high dimensional feature vectors are mapped to 2 or 3 dimensional space for data visualization. But dimensionality reduction techniques generate a model, using the same, it maps data from one space to another space where the correlation among the vectors remains same.

Dimensionality reduction here is performed in two steps:

Firstly the intrinsic dimension of the vectors is measured followed by applying a reduction on the vectors which reduces number of dimensions to number of intrinsic dimension.

Intrinsic dimension of the dataset is obtained by MLE. We also show that it has the best overall performance compared to the two other intrinsic dimension estimators. The method is explained in detail in [12]. Once dimensionality reduction is applied on any data, the distances among data points and hence the classes in the new plane, change according to the structure of the new plane. Therefore conventional classifiers fail to recognize the classes accurately as a classifier does not have a prior belief that the vectors are in different plane.

Therefore we suggest a SOM based technique for organizing and classifying the features. A SOM is essentially a technique to map data with N dimensions to a 3 dimensional lattice structure. Weight of each class is calculated using an artificial neural network based on training of the reduced vectors.

As SOM forms a cluster of the feature vectors where each cluster represents a class corresponding to the IRIS class from database, recognizing a test IRIS is essentially a problem of finding the closest cluster using linear distance formulae on the lattice plane.

According to Kohonen [11] the idea of feature map formation can be stated as follows:

The spatial location of an output neuron in the topographic map corresponds to a particular domain, or feature of the input data. More specifically:

Self-Organizing Feature maps are competitive neural networks in which neurons are organized in an 1-dimensional lattice (grid) representing the feature space. The output lattice characterizes a relative position of neurons with regards to its neighbours, that is their topological properties rather than exact geometric locations. In practice, dimensionality of the feature space is often restricted by its visualisation aspect and typically is 1 = 1, 2 or 3.

In the Proposed System a SOM is constructed with final 7 dimensions optimized through MLE intrinsic dimension estimation technique. The SOM comprises of 10x64 number of neurons for an experimental evaluation of 64 persons IRIS images.

## V. RESULTS

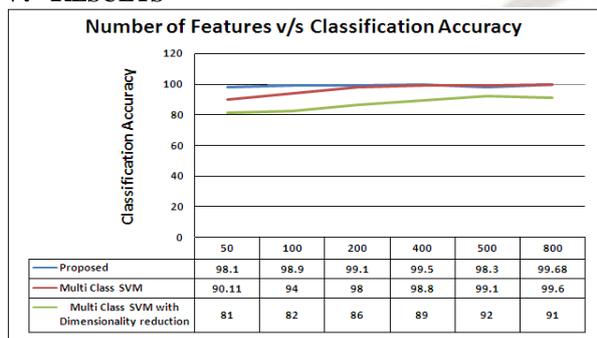


Figure 2: Classification Accuracy of proposed technique and existing techniques with different number of features. Figure 2 shows that the results obtained from proposed technique are significantly higher than kernel based classifier and are in line with the recognition rate proposed by Daugman. The graph also shows that dimensionality reduction techniques are not best suited for classification based recognition; this is due to the fact that both have different data domains.

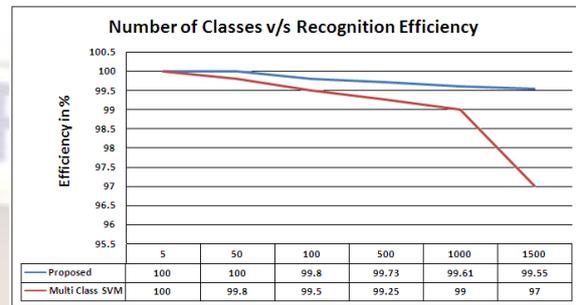


Figure 3: Comparison of Recognition Efficiency with the increase in the number of classes for proposed and Multi Class SVM based techniques.

Figure 3 demonstrates an interesting aspect, as number of classes increase kernel based technique's efficiency decreases. This is because of the increase in complexity of the kernel based classifier with increase in the number of classes. The proposed technique's complexity on the other hand does not increase since the number of comparisons is proportional to the number of classes in the proposed technique, where as in kernel based technique it is proportional to the square of number of classes without any optimization.

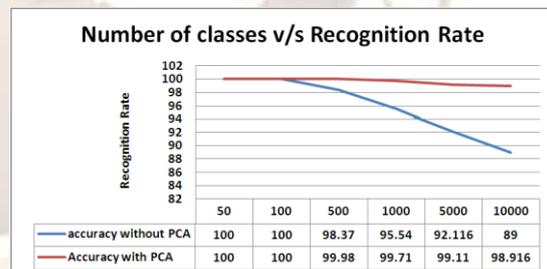


Figure 4: Comparison of Recognition rate with number of classes.

The graph shows the experimentation results of the performances of Proposed IRIS recognition system with and without an intermediate representation of feature vectors using PCA. The results clearly show that PCA aids to improvement in the accuracy. As SOM is restricted to 2 dimensions, mapping from very high number of dimensions to 2D space induces mapping errors which are largely removed with PCA. Therefore we propose to map the actual space with PCA and follow it by reducing it to 2d plane through SOM.

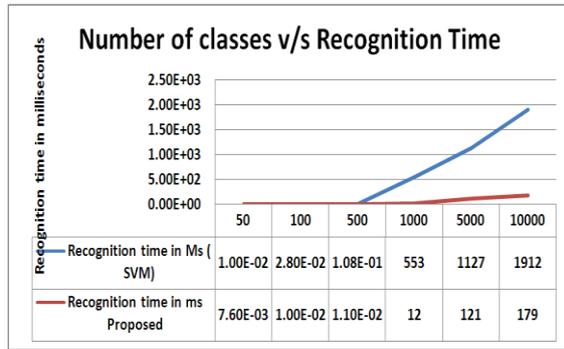


Figure 5. Comparison of Recognition Time with and without SVM Kernel.

As Matlab 'for' loops are essentially slow and require more time in execution, understanding actual time complexity of a large IRIS recognition system is difficult. Therefore C++ mex file is written for both SVM based technique and proposed system for a time complexity comparison. Daugman's technique could not be incorporated in the result for comparison as the original experiment of Daugman's technique was performed in a parallel processing environment with 32 M-array processors. The graph clearly shows that classification process which is essentially a spatial position comparison of SOM cells is much faster in the case of proposed system.

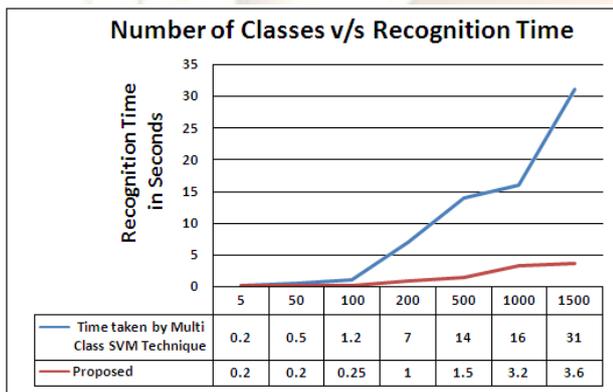


Figure 6. Comparison of Recognition time for Proposed and Multi Class SVM based Technique. Figure 6 clearly demonstrates that the recognition time for the proposed method is significantly low in comparison to the kernel based techniques. The result also strengthens the fact established by Daugman that if a linear search based classification scheme is adopted, it will give better result than any other techniques. As the proposed technique classification is merely a binary XOR operation just like the Daugman's method, it achieves considerable accuracy without compromising the speed.

## VI. CONCLUSION

Daugman's initial work with IRIS recognition is till date considered as the optimum solution for IRIS recognition. But the researches in this direction have been intense and are based on the fundamentals of considering post-segmentation coefficients of Gabor filter as non linear and unequally weighted with respect to the IRIS code. Few other researches have been carried out to select an alternative feature other than the Gabor filter coefficients. However, as not all the feature extraction techniques are non-DC, instead of using hamming distance based IRIS recognition, some authors have proposed classifier based recognition and classifiers are shown to be more time consuming than the method proposed by Daugman. Hence in this work, we propose a technique that first maps the Gabor filter coefficients to a low dimensional plane and generate a self organizing map. IRIS code generated is of length of the SOM plane (32x32=1024 bytes) where 1's are appended at every position that a particular person's class is found and 0's otherwise. Finally an IRIS code is generated for a given feature set by mapping it over the SOM plane. Recognition happens if normalized hamming distance is greater than 0.5. Results clearly show that the proposed technique achieves higher accuracy than Bhattacharya's technique with better speed due to reduced space complexity.

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