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Gender Classification from Iris using Machine Learning Techniques

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***Abstract* —The increase in the applications of biometric system, demands for a better performing system. Classification of biometric traits reduces computation and boosts performance. Iris is one of the most accurate and reliable biometric trait. Gender classification and identification of Iris is an advancing topic. With reference to previously studied methods, this paper presents with an improved algorithm for iris gender classification. Usage of ULBP and GRAB has been explored. We believe our method will achieve accuracy, higher than previously achieved till date. This suggests scope for further improvement.**

***Index Terms*— Local Binary Pattern (LBP), Generalized Region Assigned to Binary (GRAB), Local Phase Quantization (LPQ), Support Vector Machines (SVM), K-Nearest Neighbor (KNN), Ensemble, ADA boost and Decision tree.**

1. INTRODUCTION

Biometric systems are used in the Identification or Verification using various biometric traits. Namely: fingerprint, face, iris are used as biometric traits. Experiments suggest: iris performs better; achieving higher verification accuracy over other traits. This can be attributed to distinctive Iris textures. Also, very little variations in Iris over the lifespan, contributes to it being a strong biometric trait. Protected by the cornea, iris is surrounded by sclera and pupil. Human eye anatomy and Embryology research may help us understand iris. Prominent ring in the iris of Asians is used in ethnicity classification. For gender, studies suggest that female iris is shorter in diameter to male iris. Such factors could contribute to significant textural differences between male and female iris.

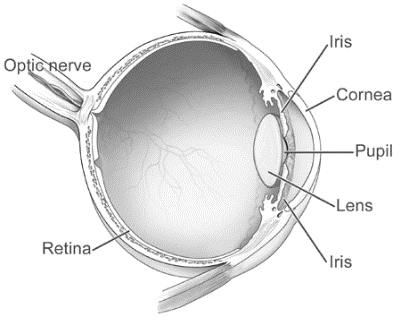


Fig. 1.Human eye anatomy.

Classification of Biometric traits is one of the most sought out problem. In recent days, with increase in population, efficient algorithms and reducing storage is of utmost priority. With gender classification, we can achieve biometric system which searches only half the database. Reduction in search space helps in reducing computations. Also, in a crime scenario, gender classification helps in reducing target suspect space. Additionally, Use of face for gender classification can be seen in user interface, marketing, surveillance. But, gender classification of iris still has a long way to go. Iris as a biometric system is more reliable than face. Thereby, in future iris gender recognition system possibly could replace face gender recognition systems. **Previous studies on gender classification of iris aren’t generic enough.** **Detailed study of such a system is necessary to bring it to a real world platform.** Therefore, identifying soft biometrics like gender, ethnicity, using iris is an emerging research area.

This paper is our first attempt to classify iris images. Firstly, considering gender classification, we experimented with various feature extraction techniques, machine learning classifiers and feature fusion techniques. Finally, we present with an improvised feature extraction algorithm for iris. We found this algorithm to produce better accuracy in gender classification than previously suggested algorithm by Tapia et al. [1] for selected database. This paper is directed towards readers trying to extract more information from texture similar to iris. Also, for readers who are working on classification using iris or related trait may find this paper useful in their research. Many figures have been presented for better understanding.

* 1. *Previous Work*

Not much work has been done to classify iris. There are only a handful of research papers, of which most focus on ethnicity.

First paper on gender classification of iris by Thomas et al. [2] used iris texture along with its geometric details. After iris normalization on images captured using LG 2200, log–Gabor filtering is applied to achieve prediction accuracy of 80%.

Second paper on iris was by Lagree et al. [3]. They were the

first to implement part wise texture extraction. But they could

achieve only a 62% for gender prediction, however an 80%

for ethnicity prediction.

Third paper on iris gender classification by Bansal et al. [4] used SVM classifier with Gaussian kernel function on statistical features. Even though they achieved 83%, their database was too small of only 800 images.

Recent paper by Tapia et al. [1] achieved accuracy of 91% for iris gender predication. They used ND-Iris Database which uses LG 4000 imaging system with NIR illumination. Their data composed of 3000 images with equal right and left iris of each subject. Using several variants of LBP, finally they showed ULBP with 50% overlap producing the highest accuracy of 91%.

Paper by Sapkota et al. [5] presented a feature extraction technique called GRAB. It consists of a LBP variant applied over series of blurred images. This technique displayed improved performance over LBP and its variants.

We experimented with results from Tapia et al [1] and Sapkota et al [5] proving the result pattern applies to our data. Then we combined both ideas producing a novice algorithm.

1. METHOD

Classification of iris involves four major steps. As shown in Fig. 2. We first capture iris images. In ND-Iris database, eye images are captured using LG2200. Then iris segmentation is performed. There are various ways in which iris is localized. Some to name: Integral differential operator, Hough transforms. After experimenting with several segmentation algorithms such as: Masek, Iris BEE software, USIT software; USIT using Weighted Average Hough and Elipsopolar Transform was adopted. Extraction of features is vastly studied and best algorithm is chosen. SVM classifier with linear basis function produces the best result.

Capture image

Segment iris

Extract features

Classify

Result

Fig. 2.Steps to classify iris.

* 1. *Iris Segmentation*

For iris segmentation, we use USIT software provided by University of Salzburg. This particular Toolkit comes with two segmentation implementations. With observation, we found Weighted Adaptive Hough and Ellipsopolar Transform–WAHET to suit our data better. Detailed information on this can be found in reference [6]. This two stage segmentation, finds the pupillary and sclera boundary separately. Then, iris is transformed from polar to Cartesian coordinates producing rectangular 30 x 360 iris texture. Let us first discuss iris localization, then

unwrapping.

First in the iris localization technique, iris center C is found using weighted adaptive Hough transform with multiple resolutions. This is deemed to be independent of database. Thereby, comparatively, WAHET segments iris better even with off–angle position of iris. Next, polar transform is used to find pupillary boundary. Edge points are fitted by an ellipse. Following, second boundary of sclera is found using Elipsopolar transform. It is seen that second ellipse boundary is concentric to first boundary ellipse. Last part of iris localization uses adaptive thresholding, region size filtering and morphological dilation to remove reflections inside pupil. Iris localization is shown in Fig. 3.

Iris unwrapping is transforming iris from polar to Cartesian co–ordinate system as shown in Fig. 4. The resulting Cartesian template is known as Daughman rectangular rubber sheet model. Different segmentation algorithms produce different dimension of rubber sheet texture templates, by using interpolation. Texture template (Fig. 5. Top two row) used in our experiments, have width of 360 and height of 30 pixels. This helps us in windowing size of 10x10. Further, you can see eyelashes and eyelids in iris template. Classifying iris with these obstructions may affect output. Therefore, efforts are made to mask these obstructions out by calculating the average positions of eyelids and eyelashes (Fig. 5. Bottom two rows). This gives us original and masked texture set.

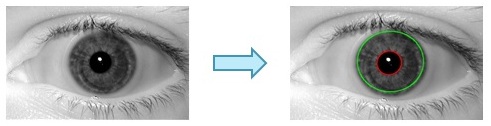


Fig. 3.Iris Localization.

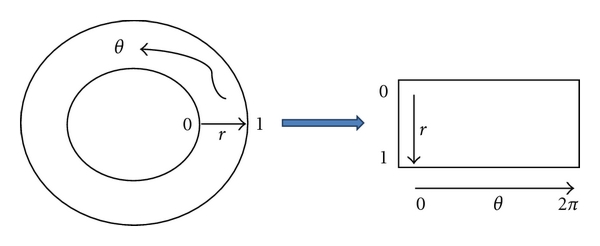
Fig. 4.Daughman rubber sheet model.









Fig. 5. Top two rows: Original data, Bottom two rows: Masked data.

## Feature extraction techniques

1. *LPQ –Local Phase Quantization*

Local Phase quantization, a grayscale image operator utilizes phase information over magnitude information. This can be explained with respect to blur and illumination. As magnitude of pixel varies with blur and illumination, phase tends to stay constant. Therefore, using phase information, we will be able achieve invariance to blur and illumination. Daughman used Gabor wavelets to extract phase information. On similar lines, Local Phase Quantization was introduced by Ojansivu et al. [7]. This reference showed LPQ to be invariant to blurring.

LPQ uses SIFT–Short term Fourier transform to extract phase information. It computes over rectangular region of *M x M* neighborhood *Nx.*

Here *f* is represented as *fx* and *w* as *wu*. Where, *wu* is basis at frequency *u* and *fx* contains all *Mx M* samples from neighborhood *Nx*.

Let *a* be a scalar frequency of first zero crossing of DFT of point spread function. In LPQ four complex coefficients are taken into consideration. These are: , , and . Consider,

}, *Im*

Now take .The corresponding 8 x M x M transformation matrix:

Implies, *Fx = Wfx*

Using covariance matrix: we get diagonal matrix *D* From: . Apply singular value decomposition to get matrix *V*, the orthogonal matrix. Further Gaussian distribution is achieved resulting in *Gx*. In order to obtain feature set we need to take histogram of integral values ranging from 0 to 255. For which quantization and binary encoding are implemented over obtained *Gx*.

Local Phase Quantization is mainly used for sharp variation of textures. It has shown higher performance over Local Binary Pattern in face classification. But in iris, texture varies smoothly. Therefore, LPQ fails to perform better than other existing feature extraction techniques like Local Binary Pattern in iris classification. Therefore, in our next section we will see various implementations of LBP.

1. *LBP –Local Binary Pattern*

Local Binary Pattern or LBP is a local feature extraction technique like LPQ. Applications of LBP are researched in [8], [9]. Characteristic feature of LBP is its dependence on the neighboring pixels. In evaluating LBP, 8 surrounding pixels of one selected pixel are considered*.* Traditional LBP is signed Compound–LBP. That is, neighboring pixels are compared in magnitude with pixel at the center.

Let us consider pixel located at *(x,y*)*.* With respect to surrounding pixels, this pixel at *(x,y*)is the center pixel. Let its pixel value be *gc* and the value of corresponding 8 neighboring pixels be *gp*. Let *s*(*x*) be 1 if *x* ≥ 0 else 0. Then,

Visually it can be seen from Fig. 6. Thresholding gives us *s(x)*after which above mentioned transform is applied. After obtaining *LBP* for each pixel in the image, it is observed that all the values lie in the range of 0 to 255. For which, histogram can be easily derived. Taking histogram reduced dimension from *m x n* image dimension to 1 x 255 if *(m.n > 255).* Such an instance of histogram is shown in Fig. 7.

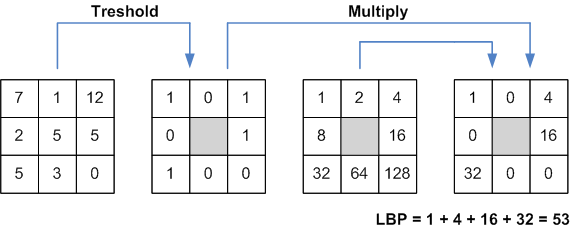


Fig. 6.Local Binary Pattern.

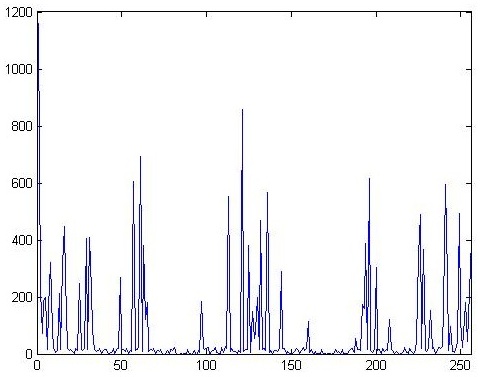


Fig. 7.Histogram.

Local binary pattern is useful to find textures such as edges, corners andother non–uniform variations (Fig. 8.). As iris is textural variation of various ridges and rings, LBP can extract these variations easily. Also, LBP being a strong local extractor is best suited to extract maximum features of iris local textures.

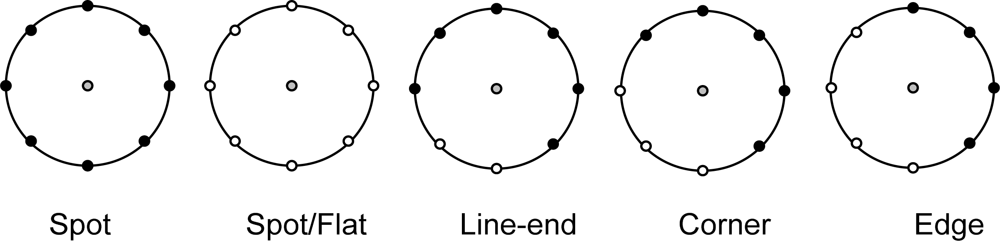


Fig. 8. LBP signed variation.

Another variant of LBP namely compound local binary pattern–CLBP for face is discussed in [10]. Above mentioned LBP is referred as signed LBP. It takes sign difference between center and neighboring pixels. But CLBP also considered magnitude difference of center and neighboring pixels comparing it with the average. However CLBP magnitude fails to perform better in case of iris. Variation in magnitude is not only due to texture but only depends on abnormalities such as: blur, shadowing and illumination. As iris is more textured than face, with small variation in texture, these abnormalities will lead to large magnitude variation. Thereby, we observed classification results dropped drastically using CLBP magnitude.

1. *ULBP –Uniform Local Binary Pattern*

Uniform Local Binary Pattern by Ahonen et al. [11] also tried to describe rotational invariance. ULBP is the extension to Local Binary Pattern. ULBP is dimension reduction of LBP. ULBP is of those sets of LBP were in there is atmost two bit transition from 0 to 1 or vice versa in the respective binary pattern. Rest LBP values are considered non–uniform patterns. The possible uniform patterns are given by Fig. 9. Therefore, first 58 bins of histogram consist of LBP values of these binary patterns and 59th bin consist of number of non–uniform patterns. This is our ULBP histogram.

It is observed that is various cases, ULBP helps in eliminating redundant features of LBP. In our results this proves to be true. ULBP outperforms LBP with higher iris gender classification accuracy.

With rotation there is circular shift in binary patterns. This can be assigned to constant by using yet another variant of Local Binary Pattern called Rotationally Invariant Binary Pattern–RILBP. RILBP assigns Uniform Binary Patterns to their minimum. By doing so, dimension reduction takes place. Out of 58 uniform configurations of binary patterns, it reduces down to 36 configurations as shown in Fig. 10. Similar technique of taking histogram as Uniform Binary Pattern is used. Therefore, in total it results in 37 bins for RILBP histogram. Using RILBP, there is dimensional reduction of*m x n* image dimension to 1 x 37 if *(m.n > 37).* However in iris gender classification, RILBP fails to perform better as it discards some important features.

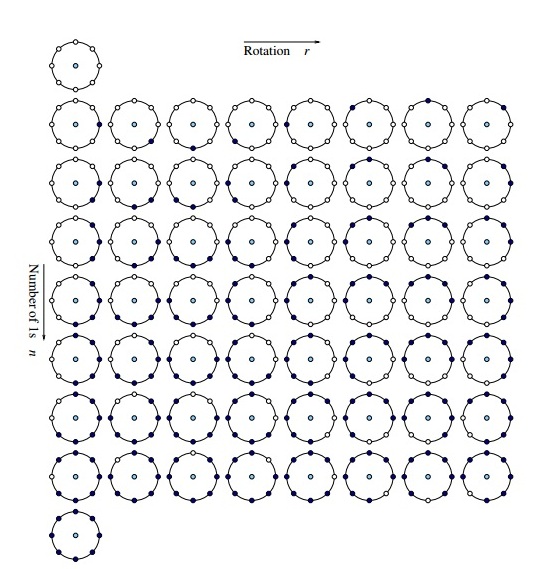


Fig. 9.Uniform Binary Pattern.

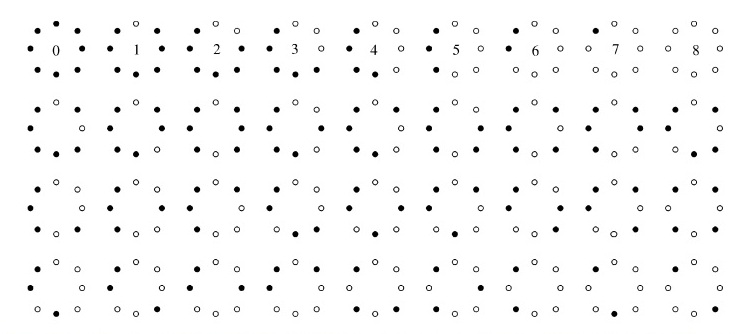
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Fig. 10.Rotatioanly Invariant Uniform Binary Pattern.

1. *Overlapping windows*

Windowing technique is common. Almost all local feature extraction techniques used windowed kernels to extract features. But overlapping kernels is introduced by Tapia et al. [1]. They achieved gender classification of 91% using ULBP with kernel size of 10 x 10 with 50%. This 91% is for their selected data. But the trend they suggested for various variants of LBP goes by: ULBP performs better than LBP, Windowing performs better than non–windowing and overlapping windows performs better than non–overlapping windows. This trend was observed to apply even to our data.

Windows extract more information as they are locally fixed around particular region. Similar consequence of overlapping windows suggest: information missed by non–overlapping windows is captured by overlapping windows.

1. *GRAB –Generalized region assigned to binary*
   1. *Fusion of Features*

There are various kinds of fusion to improve a system. Some to mention: fusion of input data, fusion of features, fusion of classifiers. General purpose of fusion is to describe a system by two or more methods when a stand-alone method fails to capture system details. That is, if a single method captures some part of the system, the other method could capture the other details of the system. Thereby, fusing these two methods will result in better understanding of the system.

In our project we perform feature level fusion. This can be better understood with the help of Fig. 11. That is, we take the top two best performing feature extraction technique and fuse them. Fusing extracted features is by appending one to another. Features resulting from Local Phase Quantization, Local Binary Patter, or Grab are the histogram values. Appending histogram of one feature extraction technique to the other results in higher dimension, but detailed feature vector. This detailed feature vector carries more information of the system and produces better classification results.

In our experimentation, fusion of top two results of ‘Uniform Local Binary Pattern–ULBP with 10 x 10 windowing and 50% overlap’ and ‘GRAB–ULBP with 10 x 10 windowing and 50% overlap’ were fused. This fusion outperformed GRAB–ULBP with 10 x 10 windowing and 50% overlap, producing the best result.

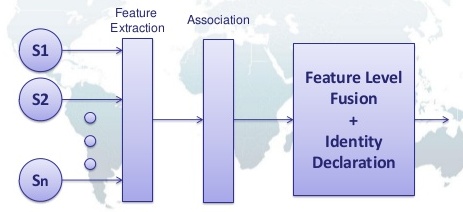


Fig. 11.Feature level fusion.

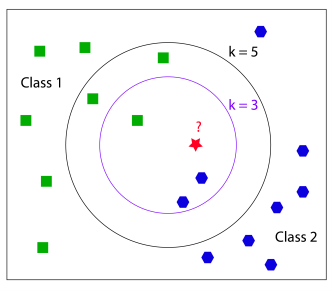
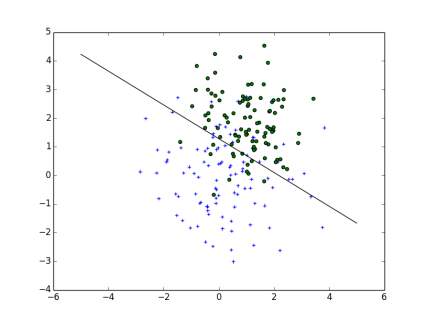
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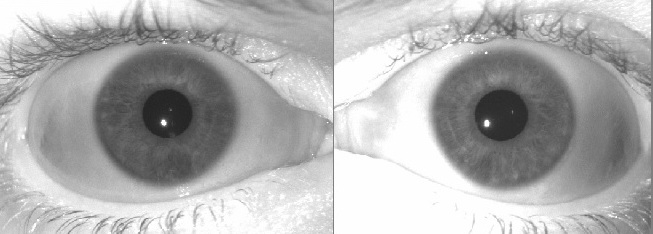
Fig. 12. Left: SVM Classifier and Right: KNN Classifier.

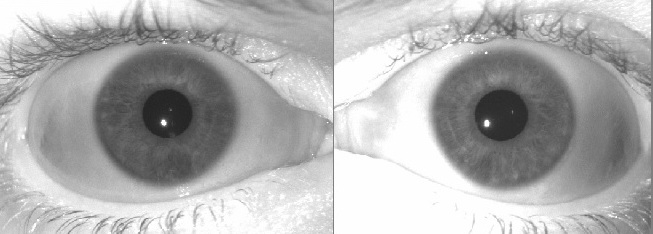
## Choice of Classifier

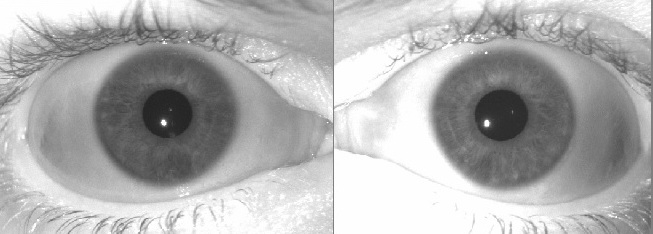
Different mathematical principles govern the rules of machine learning classifiers. We concentrate on supervisedmachine learning techniques. After experimenting with Ensemble, Decision trees, K nearest neighbor–KNN, Support Vector Machines–SVM, SVM with linear function resulted in higher classification accuracy.

Most used Machine Learning classifiers are SVM and KNN. KNN is known for its speed but SVM for its accuracy. In both the techniques n–dimensional feature vectors are represented in n–dimensional space. Thus ‘m’ feature vectors are plotted in n–dimensional space as ‘m’ separate points. As represented by Fig. 12. on the right, K as integer KNN considers K nearest points with respect to the test feature point. Thus the maximum class of k points is the classification result of KNN. Also, KNN produces varied results with variation in K.

SVM on the other hand tries to separate classes using various functions as shown in Fig. 12. on the left. Usually, Radial Basis function–RBF is deemed to perform better over linear function and Quadratic function. Additionally, Moghaddam and Yang [12] suggested SVM–RBF as the best gender classifier. However, with dimension of feature vector greater than data, RBF may produce false results. With windowing, dimension of feature vectors increases, thus we use SVM with Linear function.







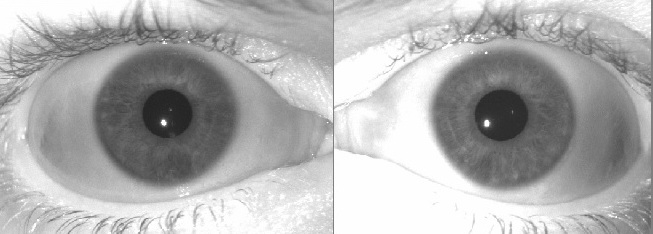


Fig. 13.Feature level fusion.

## Dataset

Data used for this project are taken from ND–IRIS–0405 image dataset. Details of this database are available at: htpp://www3.nd.edu/~cvrl/CVRL/DataSets/hmtl. Images in ND–IRIS–0405 image dataset are captured using LG–2200 imaging system. Of 356 subjects, 198 are male and rest female. Number of images for each subject is not constant. In total there are over 64,980 images.

Random images couldn’t result in reliable classification accuracy. Therefore, manually images without anomalies like blur, shadows, extended eyelashes, illumination, eyeliner and off–angle (Fig. 13, top three rows) had to be selected. Also to describe a subject accurately, both left and right iris of each subjects were considered (Fig. 13, last row). Finally we selected 194 subjects of which 198 are male and rest female. Ten images of each subject of which 5 were left iris and 5 were right. For cross validation 5 different data sets were produced by mixing. In each set we selected 4 of 5 images of each subject for training and 1 for testing. With this semi predictable data, better classification results have been achieved

* 1. *Experiments*

Using a simple local feature extractor, results in a 0 to 255 feature vector. This does not represent local textural components of the image. For which after windowing and overlapping, dimension of feature vectors increase. Dimension of each image texture is 30 x 360. The following Table. 1. Lists dimension of feature vector using corresponding feature extraction technique.

Table. 1. Feature Dimension for respective extraction algorithm

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| Feature Extraction Technique | Feature Dimension |

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For instance consider Local Binary Pattern which has 256 bins for each window. With 10 x 10 windowing of 30 x 360 image, there are 3 x 36 windows of 256 bins. So in total the dimension of feature vector is 27,648 (3 x 36 x 256). Similarly with ULBP or GRAB–ULBP 10 x 10 windowing we get 6,372 (3 x 36 x 59). But with 50% overlap we get 29,323 ((3+4) x (36 + 35) x 59).

Further, with fusion we get added number of fused feature vectors. These varied number of feature dimension help us to extract local features of the image. Thereby, various characteristic ridges, edges, corners, non–uniformity in image, are captured by these feature vectors.

1. RESULTS

Table. 1. Feature Dimension for respective extraction algorithm

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| Feature Extraction Technique | Masked | Original |

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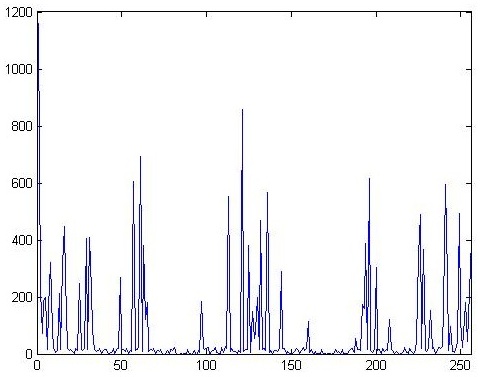


Table. 1. Feature Dimension for respective extraction algorithm

1. CONCLUSION

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