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Fuz - SVM Classifier Based Object Face Liveness Detection with Combined HOG-LPQ

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Abstract: In many real time security applications, the Object Liveness Detection and Spoof Face recognition became important. Past decades, the existing systems for Face recognition and anti-spoofing classifier is accomplished to detect object features and finds spoofing attacks on various types of objects/subjects. However, by considering the individual differences among several objects, most of the techniques were failed in finding of liveness of the test images especially in blur images. Here, we proposed a system Fuz-SVM Classifier based Object Face liveness Detection with combined HOG-LPQ which allows to select specific object based on Region of Interest (ROI) and extract features of ROI, then recognises face and later check for spoofing attacks. By considering all possible rare and uncommon fake samples like 2-D photographs, masks, reply video attacks for training, the proposed system which makes it practical to train well performed individual Object to its certain face with liveness detection and also includes not only processing of specific selected object and also extracts features of blur images. We performed experiments on various real time objects with exiting data base; the details are discussed in the prospect of the proposed approach.

Keywords: Liveness Detection, Genuine images, Spoof images, Blur images, Histogram of Oriented Gradients (HOG), Local Phase Quantization (LPQ), Region of Interest (ROI), Fuz-SVM.

I. INTRODUCTION

It is well known that face recognition systems try to validate whether the object matches with available database objects for identifying the users, while facial occlusion detection systems check the presence of any recognizable facial images for live objects. A practical face recognition system demands not only high recognition performance, but also the capability to find the liveness of current object.In recent works many general techniques were proposed to find the live object faces with non-live object faces from all its spoofing attacks. These attacks can be considered in different ways like photographs, video attacks, and 3-D face images attacks. Among the three types, the 2-D photograph images are thought to be the easiest to be used as an attacking measure and thus relevant studies have been carried out in order to suppress those attacks.

There are many approaches like single image-based approach deal with the distinctive characteristics from the ideal images taken from live faces and masks, whereas multiple image-based approach is taken from 3-D facial information and/or from eye-blink information. The locations and distributions of images vary from object to object and factual image of one object overlap the fake image of another object. Therefore, it is difficult to find non-live object with a single anti-spoofing technique which can perform well on all objects. To solve this problem, we propose a Fuz-SVM Classifier based Object Face liveness Detection with Combined Histogram of oriented Gradients-Local Phase Quantization (HOG-LPQ). These proposed system also adapted to low quality images which includes blurred images to achieve real time processing for feature matching and liveness detection.

In object face liveness detection approach, we develop anti-spoofing approach for each registered objects in database. However, many registered objects in database consisting of both genuine samples and possible fake samples. To train object face liveness models for these objects, we propose a combined Histogram of Oriented Gradients with Local Phase Quantization (HOG-LPQ) method to transfer the information provided by the objects which have both genuine images and fake images to the subjects having no fake images to synthesize fake images later these features were applied to Fuz-SVM for matching and liveness detection. The proposed method is based on the assumption that the relation between genuine samples and fake samples of two subjects are both caused by the change of identity, and thus be similar mutually. We first capturing the images and selecting Region of Interest (ROI) from captured sample image, and extracting various features from these selected images, by applying these extracted features to the fake images from live images through classifier, so that we can estimate the image whether genuine image or fake image.

In section II, literature survey on face anti-spoofing and face recognition systems with various approaches, and in Section III describes the proposed method, Section IV illustrates the experimental evaluations, and finally conclusion in Section V were explained.

II. LITERATURE SURVEY

Till to date, the existing face recognition and spoofing detection approaches can be mainly categorized into various groups and can be explained briefly as follows.

Analysis Based On Frequency AndTexture

The texture information is taken as the images taken from the 2-D objects tend to suffer from the loss of texture information compared to the images taken from the 3-D objects. In many systems for feature extraction, frequency-based feature extraction, Texture-based feature extraction and Fusion-based feature extraction are being implemented. For extracting the frequency information, at first, the authors have transformed the facial image into the frequency domain with help of 2-D discrete Fourier transform [1] then the transformed result is divided into several groups of concentric rings such that each ring represents a corresponding region in the frequency band and then, 1-D feature vector is acquired by combining the average energy values of all the concentric rings. Similarly for texture-based feature extraction [2], they used Local Binary Pattern (LBP) which is one of the most popular techniques for describing the texture information of the images. More over in fusion-based feature extraction, the system uses Support Vector Machine (SVM) classifier for learning liveness detectors with the feature vectors generated by power spectrum-based and LBP-based methods.

Analysis Based on Variable Focusing

The basic constraint of this analysis is it relies on Depth of Field (DoF) [3] which determines the range of focus variations at pixels from the sequentially taken images. The DoF is the range between the nearest and farthest objects in a given focus. To increase the liveness detection performance, the authors have increased out focusing effect for which the DoF should be contracted. In this method, Sum Modified Laplacian (SML) is used for focus value measurement. The SML represents degrees of focusing in images and those values are represented as a transformed 2nd-order differential filter. Initially, two sequential pictures by focusing the camera on facial components are being, one is focused on a first interested area particularly in face and the other is on other direction or part of the face. The first focused area is the closest to the camera lens, while the second are the farthest. The depth gap between them is sufficient to express a 3D effect. In order to judge the degree of focusing, SMLs of both the pictures are being calculated. The third step is to get the difference of SMLs.

Analysis Based on Eye Blinking and Eye Movement

The blinking-based approach for liveness detection using Conditional Random Fields (CRFs) [4] to model blinking activities, for accommodating long-range dependencies on the observation sequence. By comparing CRF model with a discriminative model like AdaBoost and a generative model like HMM. The CRF’s are probabilistic models for segmenting and labeling sequence data and mainly used in natural language processing for its accommodating long-range dependencies on the observation sequence. Blinking activity is an action represented by the image sequence which consists of images with close and non-close state.

The eye movement based system is for detecting eyes in sequential input images and then variation of each eye region is calculated and whether the input face is real or not is determined. The basic assumption is that because of blinking and uncontrolled movements of the pupils in human eyes, there should be big shape variations. In this approach, authors proposed for finding the eye region, first, Gaussian filtering to the face image is done, so that the smoothened 3D curve is obtained. To reduce the invalid eye candidates, the eye classifier, which is trained by Viloa’s AdaBoost training methods, is used. After that, face region is being normalized by about a size and rotation by using center point of eyes because the input face can vary in size and orientation. To decrease the effect of illumination, Self-Quotient Image (SQI) [5] is applied.

Analysis Based on 3D Face shape

The 3 D Face Shape based analysis [6] allows a biometric system to differentiate real face from a photo thus reducing the vulnerability and can be implemented in different scenarios either as an anti-spoofing tool, coupled with 2D face recognition systems and/or can be integrated with a 3D face recognition system to perform an early detection of spoofing attacks. These algorithm authors computes the 3D features of the captured face data to determine if there is a live face is presented in front of the camera or not. Based on the computation of the mean curvature of the surface, a simple and fast method is implemented to compare the two 3D scans. An approximation of the actual curvature value at each point is computed from the principal components of the Cartesian coordinates within a given neighborhood. The mean curvature of the 3D points lying on the face surface is then computed. The distribution of the mean curvature values for the two sets was separated, and the value of the False Rejection Rate (FRR), was computed as zero.

III. PROPOSED SYSTEM

The proposed systemFuz-SVM Classifier based Object Face liveness Detection with combined HOG-LPQgives increase in accuracy and performance of object face liveness detection. Mainly the proposed system is implemented in two stages, one is for existing data base and other is for real time data base. In first stage we capture many images with a genuine face and all its possible spoofing attacks like 2-D photograph images, reply video attacks and facial masks, then the detected face image is labelled using Local Phase Quantization (LPQ) method which not only extracts features for normal images and also includes blur insensitive image descriptor and, the labelled image is divided into non-overlapping rectangular regions of equal size and a histogram of the labels in local regions is computed independently within each region. The histograms from different regions are concatenated to build a global descriptor of the face image. By selecting a suitable features based on the mutual information between features and class labels and among features themselves is employed to select the most relevance and non-redundant features. In the training stage, selected features extracted from different training images of different categories both genuine and spoofing images are used to train the Fuzzy logic based on support vector machine classifier (Fuz-SVM). For face recognition and liveness detection, the input test images with region of Interest (ROI) and the trained classifier is employed on the selected features, and the system is shown in Fig. 1

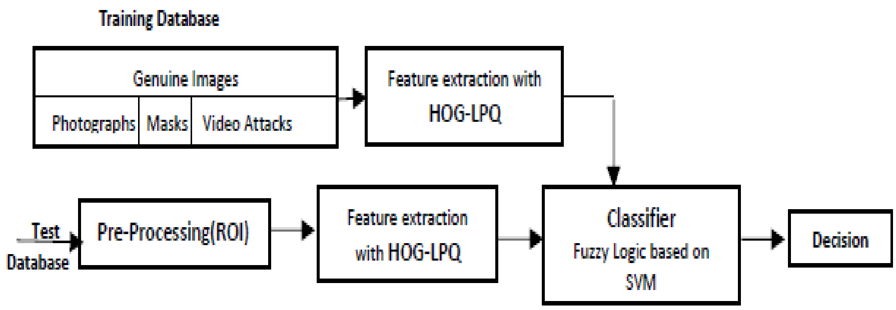

Fig.1: Proposed Object Face Liveness Detection

One of the main advantage of local phase quantization is the operator was shown to be robust to blur and outperformed the Local Binary Pattern operator (LBP) in texture classification and, we propose to employ this method as a robust feature descriptor for face images.

In the proposed system, we used two different types of features, HOG and LPQ are fused to train a classifier for face recognition. From many existed systems, we trust that the description ability of LPQ and HOG to the object is different. So, we need to determine the strength of HOG and LPQ descriptor ability on the objects or the Region of Interest (ROI) of the objects. HOG and LPQ are both based on the histogram statistics, and HOG features divides in terms of cell structure and merge in to block structure for normalization. In order to match these with LPQ, we did LPQ features statistics in to the cell structure and for the same block structure, we use Fuzzy Logic based on Support Vector Machine (Fuz.-SVM) to learn these two features to compute confidence of HOG and LPQ. Finally, we calculate the HOG-LBP features which can be well applicable to the case of the substructure of the object are not similar. In the face, because of the different sub-structures like eyes, nose, lips and chin, the description ability of HOG and LPQ are not same to partial face. Though our proposed method can be used in the detection of the Object face liveness detection and the system uses the advantages of the two features.

A. Image Acquisition and Pre-Processing

In object acquisition or capturing, can be done on various objects in different angles which includes genuine and all possible spoofing attacks like 2-D photographs, reply video attacks, mask, cut photos and many. These captured images which also includes the blurred images, so that it can avoid the difficulties at the time of matching. We have captured various Indian faces and stored it in training database consisting of genuine face images, 2-D photo face images and video reply images, showed in fig.2, fig.3 and fig.4 respectively.

Fig.2: Acquisition of various genuine object faces

Fig.3: 2-D Photo Attacks

Fig.4: Video Attacks

After acquiring various objects, the preprocessing is required because the object can be captured under many surveillance situations where there is Region of Interest (ROI) and background information in the same object. In order to detect and recognize particular object face, we use ROI tool, so that it can extract only the subset of samples within object resulting in reducing of processing time. The below fig.5, show how the ROI will work on selected object.

Fig.5: Selection of Region of Interest (ROI)

B. Histogram of Oriented Gradients

The basic principal of Histogram of Oriented Gradient (HOG) is implemented by dividing the image window into small spatial regions called 'cells', for each cell accumulating a local 1-D histogram of gradient directions or edge orientations over the pixels of the cell and the combined histogram entries form the representation of each cell. The first step is to compute the magnitude of selected ROI of the image with the help of horizontal gradient $\partial_x(x_i, y_i)$ and vertical gradient $\partial_y(x_i, y_i)$. Later the gradient can transformed to polar coordinates, with the angle $\theta(x_i, y_i)$ constrained to be between 0 and 180 degrees, so that gradients that point in opposite directions are identified. Therefore,

$$g(x_i, y_i) = \sqrt{(\partial_x(x_i, y_i)^2 + \partial_y(x_i, y_i)^2)} \quad (1)$$

$$\theta(x_i, y_i) = \arctan(\partial_y(x_i, y_i)/\partial_x(x_i, y_i)) \quad (2)$$

The second step of HOG extraction is to derive the orientation histogram from the orientations and magnitudes then normalization. HOG extraction is a single window approach, the ROI is divided into regions called blocks and, each block can be divided into cells. One histogram per cell is extracted and concatenating on each extracted cell. These cells can be either rectangular called R-HOG or circular called C-HOG. In every histogram has the same certain number of bins, which determines its precision. The bins represent the gradient orientations $\theta(x_i, y_i)$ and must be equally spaced over 0˚to 180˚ (unsigned gradients) or 0˚ to 360˚ (signed gradients). One histogram per cell is computed, each pixel in the cell contributes to the histogram adding its magnitude value to its corresponding orientation bin, this weighting value is called vote. These vote can uses magnitude values so that it will produces the best results.

One normalized descriptor per block then the overlapping can be introduced between blocks to ensure consistency across the whole image reducing the influence of local variations. On one hand, the cell histograms need to be normalized to reduce the effect of changes in contrast between images of the same object and On the other hand, overall gradient magnitude does carry some information, and normalization over a block and a block region is greater than a single cell, consisting of some information called the relative magnitudes of gradients in cells within the same block. Since each cell is covered by up to four blocks, each histogram is represented up to four times with up to four different normalizations.

C. Local Phase Quantization

The LPQ features can be extracted independently from the sets of three orthogonal planes called XY, XT and YT, and considering only the co-occurrence statistics in all possible directions (three directions) showed in fig.5, and by adding all individual histograms together then it gives a single histogram. In order to capture texture details at different aspects, we may use different sizes of the window to obtain a multiscale representation of dynamic textural content of an image sequence. Further the histograms of each plane are normalized independently so that each sums to 1 to yield a coherent representation and then concatenated to form the final HOG-LPQ descriptor.

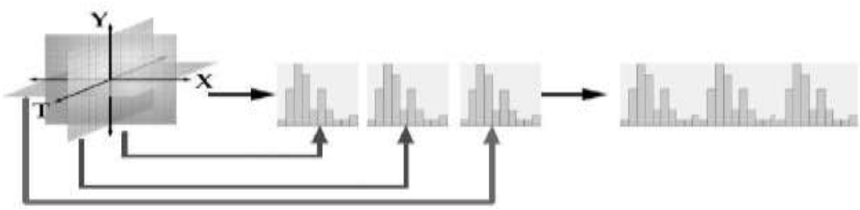

Fig. 5: Construction of a histogram on three orthogonal planes.

The local phase quantization (LPQ) is a method based on the blur invariance property of the Fourier phase spectrum uses the local phase information extracted using 2-D discrete Fourier transform or short term Fourier transform (STFT), computed over a rectangular region. The STFT over a region of N x N neighborhood of image g(x) with each position of the pixel x is defined by

$$G(u,x) \;\; = \sum_y g\,(x-y)e^{-j2\pi uTy} \quad (3)$$

$$= w_u^T g_x \quad (4)$$

Where w_u is the basis vector of the 2D discrete Fourier transform at frequency u while g_x stands for the vector containing all N^2 pixels.

From the above equation (4), we noticed that we can implement the STFT in efficient manner by using 2-D convolution $g(x)*e^{-2\pi juTx}$ for all 'u'. In the LPQ by considering only complex coefficients, corresponding to frequencies $u_1 = [a,0]^T$, $u_2 = [0, a]^T$, $u_3 = [a, a]^T$ and $u_4 = [a,-a]^T$, where 'a' is a small scalar frequency resulting

$$G^c_x = [G(u_1, x)\; G(u_2, x)\; G(u_3, x)\; G(u_4, x)] \quad (5)$$

gives each pixel location and is a vector.
Let $G_x = [Re\{G^c{}_x\}, Im\{ G^c{}_x\}]^T$, (6)
Where Re{˙} is real and Im{˙} is imaginary parts of a complex number. The corresponding 8 x N^2 transformation matrix is

$$G_x = Wg_x, \quad (7)$$

Where $$W = [Re\{w_{u1}, w_{u2}, w_{u3}, w_{u4},\} ,Im\{w_{u1}, w_{u2}, w_{u3}, w_{u4},\}]^T, \quad (8)$$

Let us assume that the image function g(x) is a result of a first-order Markov process, where the correlation coefficient between adjacent pixel values is ρ, and the variance of each sample is σ^2. Without a loss of generality we can assume that $\sigma^2 = 1$. As a result, the covariance matrix of the transform coefficient vector G_x can be obtained as

$$D = WCW^T, \quad (9)$$

Where D is decomposition matrix and not a diagonal matrix for $\rho > 0$, meaning that the coefficients are correlating.
Assuming Gaussian distribution, independence can be achieved using a whitening transform

$$H_x = V^T G_x, \quad (10)$$

Where Vis an orthonormal matrix derived from the singular value decomposition (SVD) of the matrix D that is

$$D = U\sum V^T \quad (11)$$

Once H_x is computed for all pixel positions, the information in the Fourier coefficients is recorded by binarizing the elements of H_x as

$$q_j = 1, \text{ if } q_j \geq 0, \text{ otherwise } 0. \quad (12)$$

Where q_j is the j^{th} component of the vector H_x. The resultant 8-bit binary coefficients qj are then represented as integers. Once the binary codes are obtained, a histogram of these integer values from all image positions is composed.

D. Matching

In practical security application development, used many classification methods to minimize classification errors, accuracy and speed. It is important to choose an appropriate method to solve particular task. In these concern, one of the best classification method called Support vector machine (SVM) and has been commonly used for various classification application such as feature matching with a high accuracy levels as well as great flexibility and speed. In order to attain better classification results with minimum classification error we used Fuzzy-Support Vector Machines (Fuz-SVM) in order to achieve fast and accurate classification in real time. Here we combines fuzzy logic and support vector machine method for data classification.

Let us consider the training database consisting of S number of sample images both genuine images and its respective possible spoofing images. The SVM tries to find a separating hyperplane that maximizes the margin between two classes. Maximizing the margin is a quadratic programming (QP) problem, which determining the trade-off between maximizing margin and minimizing the number of misclassified instances. To solve nonlinear classification problems, a kernel function is introduced to replace the inner product, therefore, the SVM classifier can be represented as

$$G(x) = \text{sgn}\left(\sum_{i=n} \alpha_i y_i K(x_i.x)+b\right) \quad (13)$$

where $K(x_i.x)$ is the kernel function which satisfies Mercer's theorem and Commonly used kernel functions are polynomials and Gaussian radial basic functions.

The process of Fuzzy logic (FL) is firstly, a crisp set of input data are gathered and converted to a fuzzy set using fuzzy linguistic variables, fuzzy linguistic terms and membership functions and the process is called fuzzification. Here the linguistic variables are the input or output variables of the system, a linguistic variable is generally decomposed into a set of linguistic terms. The Membership functions are used to map the non-fuzzy input values to fuzzy linguistic terms and vice versa and also used to quantify a linguistic term. Secondly, the inference is made based on a set of rules. A rule base is constructed to control the output variable and a fuzzy rule is a simple IF-THEN rule with a condition and a conclusion. The evaluations of the fuzzy rules and the combination of the results of the individual rules are performed using fuzzy set operations. The operations on fuzzy sets are different than the operations on non-fuzzy sets. Lastly, the resulting fuzzy output is mapped to a crisp output using the membership functions, in the defuzzification step. Defuzzification is performed according to the membership function of the output variable.

In our approach, we develop a Fuzzy-Support Vector Machine (Fuz-SVM) for pattern classification, which is the realization of a new idea for the adaptive kernel functions used in the SVM. The use of the proposed fuzzy kernels provides the SVM with adaptive local representation power, and thus brings the advantages of Fuzzy Logic into the SVM directly. On the other hand, the SVM provides the advantage of global optimization to the Fuzzy logic system and also its ability to minimize the expected risk; while the Fuzzy logic system originally works on the principle of minimizing only the training error. The proposed learning algorithm of Fuz-SVM consists of three phases. In the first phase, the initial fuzzy rule (cluster) and membership of network structure are automatically established based on the fuzzy clustering method. The input space partitioning determines the initial fuzzy rules, which is used to determine the fuzzy kernels. In the second phase, the means of membership functions of Fuz-SVM are optimized by using the result of the SVM learning with the fuzzy kernels. In the third phase, unnecessary fuzzy rules are recognized and eliminated and the relevant fuzzy rules are determined.

Thus in our approach, we apply the SVM technique to obtain the optimal parameters of Fuz-SVM. It is noted that the proposed Fuz-SVM is not a pure SVM, so it does not minimize the empirical risk and expected risk exactly as SVMs do. However, it can achieve good classification performance with drastically reduced number of fuzzy kernel functions.

IV. EXPERIMENTS

The effectiveness of the proposed system for Object Face Liveness Detection is tested on our own dataset consisting of genuine face images and its possible respective spoofing images and also we study the influence of various factors like image acquisition, image region, database size and etc. to the proposed system.

In all experiments, we crop the selected face images from all of training images, so that we can remove background pixels, then cropped image converted to grayscale and scaled to fixed size of pixels. The images are divided into sub categories for selecting category-specific features and for training a category specific we used Fuzzy- support vector machine classifier (Fuz-SVM). We have selected a 5 to 10 % of features out from the 100 % features are selected using combined HOG-LPQ algorithm to represent input face image with accuracy more than 99 %. This low number of features helps to reduce the computation cost and storage requirement of the system. In selection of window size, the HOG plays a special role compared to other descriptors. The local and non-overlapping windows in HOG are used directly for encoding local information. All training images from each category are used to train category-specific Fuzzy-SVM classifier using SVM library.

In the same manner, we have extracted features from all respective spoofing images and we have combined all these features using synthesizer and saved in training dataset. In our experiments, we have consider three possible spoofing attacks. Firstly, we generated features for photo attack; in this scenario, the face region from whole image is crapped and took color printout/photograph of face in 2-D. An attacker use this photograph/printout for authentication. Secondly, we consider the mask spoofing attack. In this scenario, the attacker uses 3-D mask which look likes same as a genuine face and try to authentication and third dataset consisting of high resolution videos, displayed using laptop or iPad in front of the camera. In this database, all three implementations are exist.

In our proposed system especially we focused on blurred objects, the performance of the HOG-LPQ based system was tested on images blurred artificially. We test two different blurring effects, the first one is the Gaussian blur and the other one is motion blur. All test images in the dataset were artificially blurred by convolving them with a Gaussian blur mask has the same size of the input image with $\sigma = \{0, 0.25, \ldots, 2\}$. These blurred images were then used for testing the proposed system. The same procedure is repeated for a horizontal motion blur filter with length varies from $\{0, 1, 2, \ldots, 8\}$ pixels.

To compare the robustness of combined HOG-LPQ against different local feature descriptors, the recognition rates for LPQ, LBP, and HOG features are plotted in Fig.6 for Gaussian blurred images.

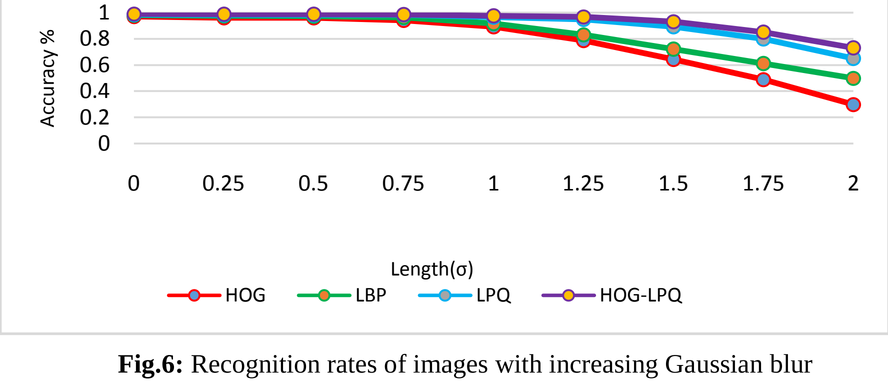

Fig.6: Recognition rates of images with increasing Gaussian blur

As it can be seen from the results, HOG-LPQ produces better results than LBP and HOG even with no blur. The LBP descriptor tolerates slight blur very well but as blur increases (σ), the recognition rate drops rapidlybut the recognition rates for HOG-LPQ, for motion blurred images again produces better results than LBP and HOG.

After performing HOG-LPQ description on both training dataset and test dataset, the Fuz-SVM classifier used to identify the liveness of the test image. The Fuz-SVM classifier which is a binary classifier which helps in discriminating the genuine object face and spoofed object face.

With our own database consisting of various objects and for the test dataset, we captured objects directly form live consisting of various individuals. For each of the above three test scenarios, the data should then be selected from the corresponding training and test sets for model training and performance reporting. To evaluate the system accuracy, we have calculated False Acceptance Rate (FAR), False Rejection Rate (FRR) and True Identification Rate (TIR), by use of these FAR, FRR and TIR, we can define Equal Error Rate (EER), and thepoint where the two lines intersect of FAR and FRR representsthe Equal Error Rate (EER) and is a very common measure of the biometric systems accuracy. Table.1 presents the details of training images, testing images and its respective FAR,FRR and TIR is given below in table.1,.

No.of Users	Training Images	Tested Images	FAR	FRR	TIR
10	85	70	21.43	4.29	95.71
15	105	103	31.43	10.00	97.09
20	100	105	25.71	5.71	92.38
25	120	115	22.86	8.57	96.52
30	140	135	41.43	11.43	96.30
40	150	120	30.00	12.86	90.83

Table.1: Performance of the Face Spoof detection using Face images

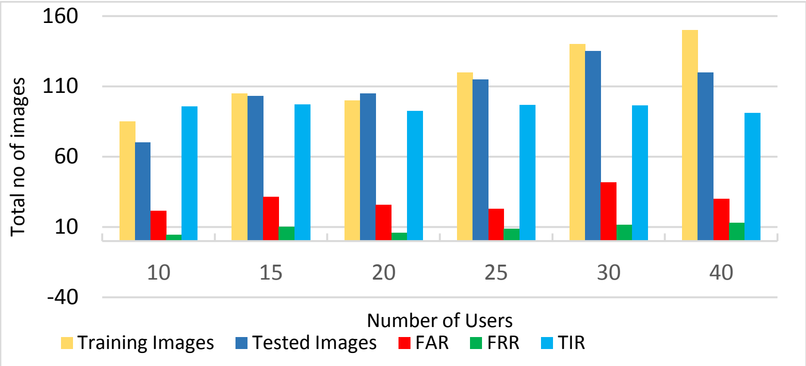

Fig.7: Performance of the proposed system

Tested images	TIR (%)
70	95.71
103	97.09
105	92.38
115	96.52
135	96.30
120	90.83

Table.2: True Identification Rate for number of tested images

Fig.8: Accuracy of Liveness detection

V. CONCLUSION

We proposed a new Fuz-SVM Classifier basedObject Face Liveness Detection with combined HOG-LPQ for liveness detection and anti-spoofing including for blur images. The combined HOG-LPQ features is experimentally proved to be very efficient to recognize various kinds genuine and spoofing attack objects. The comparison of HOG-LPQ with other local features descriptors such as local binary pattern (LBP) and histogram of gradient orientation (HOG) made, showsimproved in accuracy with HOG-LPQ for all type of training and test images. Moreover in the classifier state, we used Fuz-SVM provided high accuracy in identifying of genuine and spoofing objects from the various attacks for liveness detection. The combination of HOG-LPQ feature selection method and Fuz- Support Vector Machine gives a comparable results with other state-of-the-art methods. The recognition rate and accuracy can be further improved by considering various test datasets.

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