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Kernel-based scale-invariant feature transform and spherical SVM classifier for face recognition

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ABSTRACT

Due to the wide range of commercial and law enforcement applications and the availability of feasible technologies, face recognition has recently gained significant attention among the researchers. The literature presents various face recognition systems, which are capable of measuring and matching the distinctive features intended for the purpose of identifying or verifying a person from a digital image. The identification of distinctive features from the face image poses various challenging aspects due to the various poses and illumination conditions. To overcome these major limitations in the existing methods, this paper proposes kernel-based Scale-Invariant Feature Transform and spherical SVM classifier for face recognition. Furthermore, a novel weightage function for feature extraction and classification, which is termed as Multi Kernel Function (MKF), is also proposed. To extract facial features, we adopt SIFT technique, which is modified in the descriptor stage by the proposed MKF weightage function, thereby evolving a new technique which we termed as KSIFT. Multi-kernel Spherical SVM classifier is used for the classification purpose. The performance of the proposed method is analyzed by performing experimentation on CVL Face Database for the evaluation metrics, such as FAR, FRR, and Accuracy. Then, the performance is compared with the existing systems, like HOG, SIFT, and WHOG. From the experimental results, it can be shown that the proposed method attains the higher accuracy of 99% for the face recognition system.

Keywords: SIFT feature, kernel function, Feature extraction, Classification, Recognition.

1. INTRODUCTION

Nowadays, facial recognition (FR) system has a vital part in the security system in several applications, like surveillance, access control, image understanding, and so on. The facial recognition system is employed to verify the person's identification using an artificial system (Lenc & Král, 2015). The facial recognition is performed by comparing the facial features against a facial database. Thus, the face recognition system provides the person's identity verification in a natural and easy method. The face recognition system has four stages, namely, 1) Face Detection, 2) Feature Extraction, 3) Classification, and 4) Face Recognition. The last two phases are combined together. In face detection, the face image is detected by the methods, as appearance based method, template matching method, knowledge-based method, and so on. In feature extraction stage, the features, such as lips, nose, and eyes, are extracted from the face for distinguishing people from each other. The methods, such as Gabor Filter, JPEG (DCT Zigzag), and DCT, are used for feature extraction. In face recognition/classification, the face image is matched with the existing face image stored in the database. The methods, as neural network, HMM, SVM, and so on, are used for face recognition (Richa and Jagroop Kaur Josan, 2015). The captured images degrade the performance by variations, such as different poses, occlusion, background, illumination, resolution, and facial expressions. In face matching stage, these variations lead to mitigate the similarity between the face images, which provides fault identification of the face image (Narang *et al.,* 2013).

Basically, face recognition methods are classified into two groups, namely, (1) Appearance based (holistic) and (2) feature based approach. In the holistic approach, the face data is extracted in the form of high dimensional face information. Then, the high-dimensional data is converted into a lower dimensionality space for further processing using some dimension reduction methods, like Principal Component Analysis (Soldera *et al*., 2015), Linear Discriminant Analysis (Li *et al.,* 2007). In feature based approach, the local features, such as eyes, nose, and mouth, are extracted and their locations and local statistics (geometric and/or appearance) are fed into a structural classifier (Divyarajsinh N. Parmar & Brijesh B. Mehta, 2013). Some methods, like Gabor method (Huang *et al.,* 2015) and SIFT based methods (Susan *et al.,* 2015; Vinay *et al.,* 2015), are utilized for the feature based approach. A big challenge for feature extraction methods is feature "restoration", which occurs when the system tries to retrieve features that are invisible due to large variations, for example, head Pose when we are matching a frontal image with a profile image (W. Zhao *et al*., 2003; Divyarajsinh N. Parmar & Brijesh B. Mehta, 2013). Even though schemes of all these types have been successfully applied to the task of face recognition, they have certain advantages and disadvantages. Thus an appropriate scheme should be chosen based on the specific requirements of a given task.

Scale Invariant Feature Transform (SIFT) method was presented by Lowe. In face recognition system, the SIFT based approach is more unique and has many properties, which acquire the better face matching method in the recognition system (Lowe, 1999). Initially, the SIFT based approach was designed only for the object recognition purpose. Nowadays, SIFT features are utilized in certain pattern recognition applications (Lowe, 2004) like automatic speech recognition, recognizing iris and human face, identifying fingerprint, etc. SIFT has some problems. First, the number of SIFT features that are generated from an image cannot be controlled. Generally, two face images have different number of SIFT features. Owing to this problem, SIFT features cannot be used with standard machine learning tools, like Support Vector Machine or Neural Net. The second problem is computational complexity; SIFT features are of high dimension. Matching a large number of high-dimensional features among all images in a database is time consuming.

The major goal of this paper is to enhance the accuracy of the classification of face recognition using the multi-kernel based SIFT feature and spherical SVM classifier. Here, various individual face images are considered. The proposed methodology consists of three steps, such as pre-processing, feature extraction, and spherical SVM classifier. Initially, the input face images undergo resizing operation, which is done in the pre-processing steps. The resultant image is fed into the further steps. Subsequently, the features are extracted by the kernel based SIFT feature. The SIFT feature is used to extract the features by the following four stages, that is, extreme detection, key points removal, orientation assignment, and calculation of descriptor. In the descriptor stage, we extract the facial feature using a newly developed weighting function, which consists of multi kernels, such as logarithmic, tangential, and exponential functions. Hence, the proposed SIFT feature is named as kernel SIFT (KSIFT). After the features are extracted using the proposed KSIFT, it is then given to the spherical SVM classifier. This classifier is also proposed based on the newly evolved function. Finally, the multi-kernel spherical SVM classifier is utilized to improve the recognition rate.

The major contributions of this paper are as follows:

- A new weightage function (MKF) is designed with the help of different kernel functions, such as logarithmic, exponential, and tangential functions.
- The KSIFT feature and the multi-kernel spherical SVM classifier are presented for face recognition depending on the newly developed multiple kernel function.

This paper is structured as follows: Section 2 discusses about the feature extraction approaches and classification algorithms for face recognition system from nine research papers, motivation, and challenges of this work. Section 3 briefly explains the newly evolved multiple kernel function. The proposed methodology for facial feature extraction using KSIFT feature and recognition by the multi-kernel based spherical SVM classifier is described in section 4. The experimental results and performance evaluation analyzed for the face recognition system are shown in section 5, and the paper is concluded in section 6.

2. LITERATURE SURVEY

Although techniques of all these types have been successfully applied to the task of face recognition, they have certain advantages and disadvantages. In this section, the various research papers in face recognition are discussed and the benefits and drawbacks of each paper are described.

Peter N. Belhumeur *et al.* (1997) have formulated an algorithm for facial recognition, in which huge deviation in the facial expression and direction of light did not affect the performance. This approach depends on Fisher's Linear Discriminant and generated best-separated classes in a low-dimensional subspace in the situation; even there is a big deviation in the facial expression and the direction of light. The same computational requirements are crucial for the Eigenface approach, which is another technique that depends on linear projection of the image space in a low dimension subspace. From the experimental results, it was concluded that the error rates of the "Fisherface" approach are less than the Eigenface approach. Due to the similarity measure between the images, face matching was done successfully. However, the performance was reduced when the image had the scale and affine variations with large databases.

Stan Z. Li *et al.* (2007) have solved the illumination invariant face recognition problem for the indoor, cooperative-user applications. Initially, an active near infrared (NIR) imaging system was proposed, which was capable of producing fine quality face images without considering the visible lights in the surroundings. Then, they utilized the local binary pattern (LBP) features for compensating the monotonic transform, thereby developing an illumination invariant face representation. Subsequently, they presented the face recognition techniques using NIR images. Then, they presented an approach that is capable of achieving face recognition accurately. Experimental results show that the higher accuracy was obtained based on invariant representation, but the performance was poor for the image captured with sunlight for the face recognition.

John Soldera *et al.* (2015) have proposed a face recognition approach, which depends on projecting the face image representations of higher dimensionality into lower dimensionality and highly discriminative spaces. In order to achieve this, modified orthogonal locality preserving projection (OLPP) method was used. This approach performed well with both sparse and dense face image representations and had the tendency to be robust against data outliers and noise. Moreover, they have introduced a sparse representation for preserving the details and compensating the uncertainties features. Five public datasets were used for the experimentation, and they recommended that this technique is capable of providing better accuracy values for full low-resolution grayscale face images, but the OLPP method attained less accuracy while using grayscale images.

A new face feature called Line Edge Map (LEM) was created by Yongsheng Gao and Maylor K.H. Leung (2002) for face coding and recognition. A detailed study was done to cover all the characteristics of human face recognition, such as controlled or ideal condition and size deviation, changing the lighting condition, changing the facial expression, and changing the pose. They have also presented a face prefiltering approach to accelerate the searching process. By comparing with the Eigenface method, this method performed well in many of the experiments. Hausdorff distance measure provided a better technique for face coding and recognition. It improved the search speed in face matching stages, but it is not suitable for sparse representation.

Depending on locality repulsion projections (LRP) and sparse reconstruction-based similarity measure (SRSM), Jiwen Lu et *al*. (2013) have presented a technique to deal with the issue of SSPP face recognition using multiple probe images. SRSM technique was proposed for distinguishing the correlation among the gallery face and the probe image set. Five commonly used datasets were used for the experimentation, and they have illustrated the efficiency of this method. The LRP method achieved the better recognition rate, but it contained the limited discriminative feature based face matching.

Zheng-Hai Huang *et al.* (2015) have explained a face recognition approach by utilizing two-dimensional discrete wavelet transform (2D-DWT) and a patch strategy. They have proposed a non-uniform patch strategy for the top-level's low-frequency sub-band. By employing this patch strategy to all samples, they obtained the patches of training samples and testing samples. Then, they provided the conclusion by utilizing the nearest neighbour classifier and the majority voting. The results show that the face recognition technique outperformed the conventional 2D-DWT method and other well-known patch based techniques. It enhanced the performance in frontal or near frontal facial images. The drawback here is the performance degradation with the change in the pose of the images.

Varun R. *et al.* (2015) have presented a feature extraction approach depending on Hough Transform peaks. In facial recognition system, each stage was analyzed, and an effort was taken to enhance each stage. For extracting the features efficiently, Block-wise Hough Transform Peaks were utilized. The feature space for optimal feature subset was searched based on Binary Particle Swarm Optimization (BPSO). From the experimentation, it was concluded that this system outperformed other FR approaches in terms of the illumination variations, which usually present in face images. It had the high performance rate and but it requires more computation time.

Huiyu Zhou and Abdul H. Sadka (2011) have proposed a technique for integrating spatially structured features into a histogram-based facial recognition. In this technique, during the computation of diffusion distance on a pair of facial images, its shape descriptions were constructed by the Gabor filters, which contain several scales and levels. It demonstrates that using perceptual features by combining Gabor filtering and diffusion distance improves the performance of the system considerably. The discriminative representation of the image was then utilized for the classification of human faces in the database. It was utilized to handle alignment, distortion, and quantization of images to obtain better recognition rate but this method did not consider the color and intensity variation of the face images.

2.1 Motivation

Based on the literature review made, the following challenges are listed out from the different techniques.

- The human face images have variations, like appearance, poses, facial expression, ageing, owing to illumination, rotation, translation, scale, particular occlusions and limited training samples are main challenges in face recognition (Li *et al.,* 2007; Gao & Leung, 2002; Varun *et al.,* 2015).
- Feature extraction technique used for the face recognition system is also challengeable (Zhou & Sadka, 2011; Zhang *et al.,* 2007). The feature extraction technique must extract all the discriminative features corresponding to the facial image without any negligence.
- The important challenge is to utilize the features effectively for classifying the person. The classification algorithm should be able to differentiate the person accurately by using the extracted features from the face images.
- The original images are of high resolution, but there will be a significant deviation in the size of the faces. Recognizing such images is not an easy task. Furthermore, handling some other features, such as clothes, part of the face obstructed by the hair, facial hair, etc., are also the difficult tasks to be considered (Abiantun *et al*., 2014).

2.2 Problem definition

In general, individuals are identified by their face. Hence, face identification has recently gained significant attention among the researchers. Nowadays, face identification is performed automatically with the development of technologies. Here, the major goal is to identify the person by analyzing the face image. The input face image is matched with the face images presented in the database to identify the person. The face identification is mainly used in security applications. Let us assume the face image database I which is constructed with r number of face images.

$$I = I_t,\ 1 \le t \le r \tag{1}$$

where I is the face image database, which consists of r number of individual face images. The input face image is matched with these r number of face images in order to identify the corresponding person of the input face image.

3. DESIGNING A NEW MULTI KERNEL FUNCTION FOR SIFT FEATURE AND SPHERICAL SVM CLASSIFIER

Depending on the motivation, this paper proposes the kernel based scale-invariant feature transform and spherical SVM classifier for face recognition to overcome the challenges of the existing research works. Here, a new weight function called multi-kernel function is utilized for feature extraction and classification. There are four stages in SIFT feature extraction, such as extrema detection, keypoint localization, orientation assignment, and descriptor calculation. Generally, in SIFT feature, the descriptor calculation is done by the Gaussian weight function. To enhance the better performance recognition rate, we propose a new weightage function named as multi-kernel based scale-invariant feature transform (KSIFT). The multi-kernel function is described below.

Normally, the kernel function is used to operate the high-dimensional data, and then the features are extracted implicitly without calculating the coordinates of data rather than the inner products computation among the images of all pairs of data in the feature space. However, the kernel function does not have the capacity to handle the large datasets. So, we use different kernel functions instead of a single function for feature extraction and classification. The multi-kernel function is a non-linear learning method, which aims to generate a kernel function where the kernel is a linear combination of fixed base kernels. This kernel function is used to learn the weighting coefficients in every base kernel rather than optimising the kernel parameters of a single kernel. The advantage of the multi-kernel function is that the feature combination and classification are done simultaneously. Also, different data formats are utilized in the same formulation to enhance the interpretability of the decision function and performance.

Furthermore, a new weightage function is proposed for the local key descriptor in KSIFT feature and spherical SVM classifier for better recognition rate. Then, the multi-kernel functions, like logarithmic, tangential, and exponential functions, are utilized to design a new weightage function. These different kernel functions have different characteristics and different influence on the effects of face recognition in order to achieve high recognition efficiency. Hence, this kernel function is named as the multi-kernel function (MKF), and it is expressed as

$$k = \alpha \log\left(\|i - j\| + 1\right) + \beta \exp\left(-\frac{\|i - j\|}{2\sigma^2}\right) + \gamma \tanh\left(\eta i^T j + c\right) \tag{2}$$

where α, β and γ are the constants and *log, exp* and *tanh* are the logarithmic, exponential, and tangential kernel functions, respectively, i and j are the features, $\|\bullet\|$ is used to determine the Euclidean distance. k is the multi-kernel function. The proposed multi-kernel function is used to estimate the best similarity measures by optimizing the weights of a set of kernel functions and also reducing the objective function at the same time.

i) Logarithmic kernel function: This kernel seems to be more interesting for images, but it contains only the condition positive definite. The logarithmic kernel function is utilized where the mapping function is done. The logarithmic kernel density estimation processes are more commonly employed for estimating the density function, and they perform in a better way in several situations. Thus, the logarithmic transformation of the data provides better performance.

ii) Exponential kernel function: It is a popular kernel function used in various kernelized algorithms. Particularly, it is used for SVM classifier. The feature space of the exponential kernel function contains an infinite number of dimensional feature spaces. The exponential kernel is used to map the samples into another dimensional space when the data is non-linear separable. This function is also used to enhance the classification accuracy. The exponential kernel is recognized by the Euclidean distance between the two feature vectors. This function is widely used because it has a wide range of convergence and applicable to low-dimensional, high-dimensional, small and large sample size.

iii) Tangential kernel function: This kernel function is quite popular due to its origin from the neural network theory where the bipolar sigmoid function is commonly used as the activation function for artificial neurons. The hyperbolic tangential function is also known as the multilayer perceptron kernel. The tangential kernel function contains two parameters, such as scaling parameter, i.e., slope η and shifting parameter, i.e., intercept c. Although this function contains only conditionally positive definite, it performs well in the feature extraction and classification.

4. PROPOSED METHODOLOGY: FACE RECOGNITION USING KERNEL BASED SIFT FEATURE AND SPHERICAL SVM CLASSIFIER

To enhance the accuracy of the classification of face recognition system, this paper develops a novel method for facial recognition using kernel-based scale-invariant feature transform (SIFT) and spherical SVM classifier. Figure 1 illustrates the block diagram of our proposed method. Initially, in our proposed work, we develop a new weightage multi-kernel function using logarithmic, exponential, and tangential kernel functions. The proposed methodology for face recognition is described by the following three steps: i) Preprocessing, ii) Feature extraction, and iii) spherical SVM classifier. At first, the input face image is fed into the preprocessing step, which makes the image to be suitable for further steps. From the preprocessed image, the facial features are extracted by the proposed multi-kernel based SIFT (KSIFT) features. Normally, the SIFT feature includes four stages, that is, extrema detection, removal of key points with low contrast, orientation assignment, and descriptor calculation. In our proposed system, the features are extracted by the key point descriptor stage of SIFT using the newly designed weighting function, which is termed as KSIFT (kernel-based SIFT). After extracting the features using KSIFT, the features are given into the classifier to classify the face image for recognition. Finally, the spherical SVM classifier is proposed based on the newly designed multiple kernel function for the face recognition.

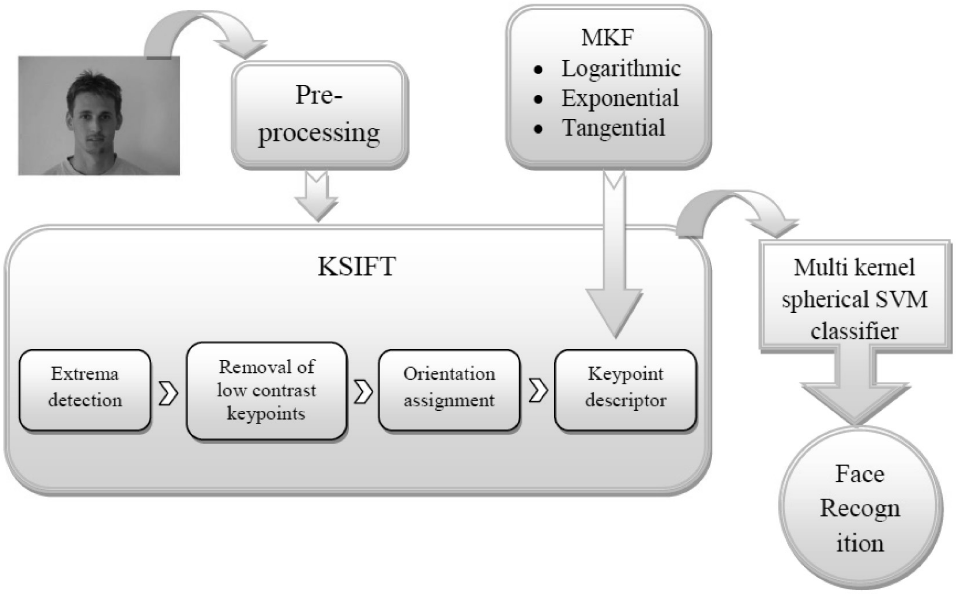


Fig. 1. Block diagram of the proposed method.

4.1 Pre-processing

Initially, the input face image undergoes the pre-processing step. Pre-processing is used to enhance the quality or the visual appearance of the image. Pre-processing includes normalization, masking, and resizing. Figure 2 shows the sample input images of the individual face image. In this paper, consider the face image database I with r number of face images. The input face images are pre-processed by the resizing operation. Thus, the pre-processed image is obtained, which is used for the feature extraction.

Fig. 2. Input images.

4.2 Feature Extraction

The facial features are extracted from the pre-processed image using the proposed multi-kernel based SIFT feature. The SIFT (Lenc & Král, 2015) feature contains four stages, such as scale-space extrema, key point localization, orientation assignment, and key point description. The proposed multi-kernel based SIFT feature is utilized for facial feature extraction. The KSIFT feature extraction method is explained below.

4.3 KSIFT

The SIFT (Scale Invariant Feature Transform) (Lenc & Král, 2015) feature extracts and describes the local features of facial images for face recognition. It is advantageous than other methods in the fact that it is used to identify the features robustly even if the image contains clutter and occlusion since the SIFT feature descriptor is invariant to uniform scaling, orientation, affine distortion, and illumination changes. It includes four crucial steps, which are explained below. In this proposed technique, the feature is extracted in the keypoint descriptor step using the new weighted function of multi-kernel. Hence, our proposed SIFT feature is named as KSIFT (kernel-based SIFT) feature.

a) Scale space extrema detection: The scale and the image locations are computed in this stage efficiently by applying difference-of-Gaussian function to find the potential interest points. Then, the location is detected by a continuous function of scale called as scale space. Thus, the scale space of an image is given by

$$S(x, y, \delta) = G(x, y, \delta) * I(x, y) \tag{3}$$

where * is the convolution operation, $I(x, y)$ is an input image, and the Gaussian function is expressed by

$$G(x, y, \delta) = \frac{1}{2\pi\delta^2} e^{-\left(x^2+y^2\right)/2\delta^2} \tag{4}$$

Subsequently, the DoG (difference of Gaussian) is evaluated by computing the difference of Gaussians of two scales that are separated by the factor *f*. Thus, the DoG is expressed by the convolution operation of input image with a constant multiplicative factor *f*,

$$H(x, y, \delta) = \left(G(x, y, f\delta) - G(x, y, \delta)\right) * I(x, y) \tag{5}$$

$$H(x, y, \delta) = S(x, y, f\delta) - S(x, y, \delta) \tag{6}$$

where $I(x, y)$ is an input image, $G(x, y, \delta)$ is the Gaussian function, and $S(x, y, \delta)$ is the scale space of an image.

To determine the key point, the iteration is done throughout the pixels that are compared against their eight nearby neighbor pixels and nine neighbor pixels at lower scale and higher scale. If the pixel value is either lower or higher when compared with all of its neighbor pixels, then the pixel is determined as the key point.

b) Removal of low contrast key points: The above extrema detection method provides many key points; some of the key points are either unstable or of low contrast. During this stage, the low contrast key points and poorly localized edge points (unstable) are removed. At first, the interpolation is used to determine the accurate position for each key point. Thus, these key points are generated based on their stability measurement, and the interpolation is done in difference of Gaussian, which is represented as follows:

$$H(u) = H + \frac{\partial H^T}{\partial u} u + \frac{1}{2} u^T \frac{\partial^2 H}{\partial u^2} u \tag{7}$$

where H and its derivatives are estimated at the sample point and $u = (x, y, \delta)$ is the offset from this point. This information is used to remove the low contrast and unstable key points.

i) Once the key point is localized, the location of the extremum, $\hat{u}$ is defined by

$$\hat{u} = -\frac{\partial^2 H^{-1}}{\partial u^2} \frac{\partial H}{\partial u} \tag{8}$$

If the extremum value is less than the threshold value, this indicates that the contrast of the key point is low. Then, by comparing with the threshold value, the low contrast key point is removed in this stage. Thus, the derivative function at the extremum $\hat{u}$ used for the rejection of the unstable extrema with low contrast key point is

$$H(\hat{u}) = H + \frac{1}{2} \frac{\partial H^T}{\partial u} \hat{u} \tag{9}$$

ii) The principal curvature is evolved to remove the unstable key points. The principal curvature is evaluated at each key point to explore the inadequately localized edges in the difference of Gaussian function. Thus, the principal curvature is represented by Hessian matrix as

$$M = \begin{bmatrix} H_{xx} & H_{xy} \\ H_{yx} & H_{yy} \end{bmatrix} \tag{10}$$

where the values in the matrix are estimated by the derivative function of differences of neighbor sample points. Then, the ratio of principal curvature for each key point is defined by the Eigen values and the determinant of the matrix. If the ratio is above the threshold value, then the poorly localized key point is removed; otherwise it is kept for orientation assignment.

c) Orientation Assignment: After the key point is localized, one or more orientations are assigned depending on the local image gradients. Then, the key point descriptors can be signified with respect to the assigned orientation, scale, and location for each feature. The orientation assignment is generated by using the key points scale to choose the Gaussian smoothed image. For each sample image $S(x, y)$ with the scale δ, the magnitude and orientation (Lenc & Král, 2015) are represented by

$$m(x, y) = \sqrt{(S(x+1, y) - S(x-1, y))^2 + (S(x, y+1) - S(x, y-1))^2} \tag{11}$$

$$\theta(x, y) = \tan^{-1}\left(\frac{S(x+1, y) - S(x-1, y)}{S(x, y+1) - S(x, y-1)}\right) \tag{12}$$

d) Key point Description: After orientation assignment, the consequent step is the computation of a descriptor for the local image region that is highly distinctive. The magnitude and orientation are evaluated using the scale of a key point in the orientation assignment stage. Then, with respect to the key point orientation, the coordinates of the descriptor and the orientations are rotated, which are used to exploit the orientation invariance. In the existing

SIFT feature, the Gaussian function is used with the magnitude to determine the weight of each sample point. It is represented by $m(x, y) * G(x, y)$, where G is a Gaussian function. But, the drawback of using Gaussian function is that it could not preserve the image brightness, providing less emphasis to gradients since they are away from the centre and also affected by misregistration errors.

Hence, in KSIFT feature, we utilize the proposed multiple kernel functions instead of the Gaussian weighting function. The multi-kernel function is used to increase the variance and conquer the fine scale structures without generating any artefacts in the image. It also mitigates the computational complexity. Thus, the weighted function in KSIFT for feature extraction is given as

$$X = m(x, y) * k(x, y) \tag{13}$$

where m is the gradient magnitude and k is the multiple kernel function, which includes logarithmic, exponential, and tangential kernels. The key point descriptor is shown in figure 3. The orientation histograms are generated over 4×4 sample regions with respect to the significant shift in gradient positions. Figure 3 shows the eight directions of gradient which are denoted by arrow, and then the arrow length is based on the magnitude of histogram.

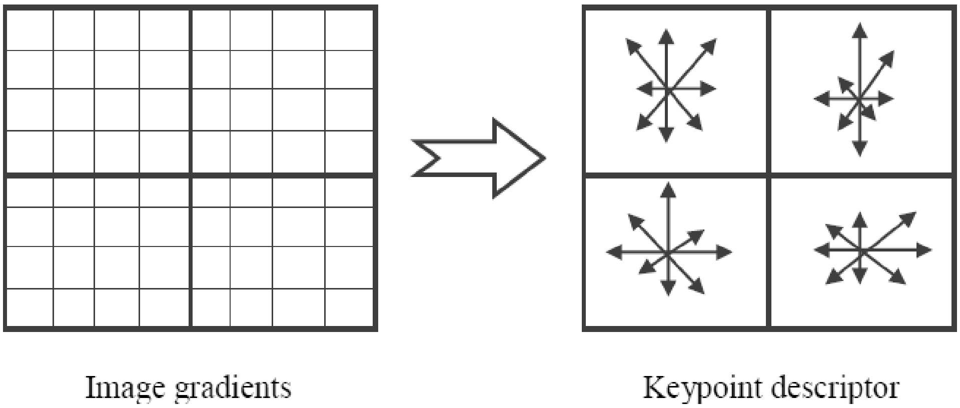


Fig. 3. Key point descriptor array.

The proposed KSIFT exploits the better performance with the 4×4 array. In each array, the eight orientation bins are utilized. Then, the feature element of each key point is generated by $4 \times 4 \times 8 = 128$. Thus, the feature vector is created by the concatenation of the values of all the orientation histogram entries, which corresponds to the length of the arrow.

4.4 Multi kernel based spherical SVM classifier

Once the features are extracted by KSIFT, then they undergo classification. Here, the kernel based spherical SVM classifier is employed. It is a supervised learning method for classification. The SVM is a binary classifier, which has less ability to handle large datasets. Since the SVM classifier can only classify the data in a linear separable feature space, the kernel-function is used here to induce such a feature vector by implicitly mapping the training data into a higher dimensional space where the data is linear separable. The multi-kernel based spherical SVM classifier (Strack *et al.,* 2013) is utilized in this paper. The spherical SVM classifier is employed by using two approaches, that is, convex hulls and enclosing ball techniques. In spherical SVM, the enclosing ball approach is used to handling the large datasets. Between two classes, evaluating the maximum margin is difficult for finding two closest points, which lead to the overlapping of classes. Thus, the reduced convex hull method is used to create the margin between two classes and separating them. However, the spherical SVM contains only one kernel function called as an exponential function.

In this paper, we propose the multi-kernel, which is newly developed for spherical SVM classifier to improve the facial recognition rate. The use of multi-kernel is defined by i) to find the best solution, the multi-kernel function consists of different kernels, which are used to combine the data from different sources that have different notions of similarity, and ii) the parameters are selected to an optimal kernel from the large kernel set, which allows more automated machine learning methods. Thus, our multi-kernel spherical SVM classifier consists of three kernel functions, which are logarithmic, exponential, and tangential functions.

i) Initially, the violating vectors are found, and the stopping criterion is the same. Then, the centre of the enclosed ball is initialized randomly, which is represented by

$$C = \sum_{i=1}^{h} W_i X_i \tag{14}$$

where C is a cluster centre, X_i is a feature vector, h is the number of features, and W is defined as the weight. Initially, the weight W can be represented as zero and one. Then, n_s is defined as the size of the random subset, n_a is referred to as the number of draw attempts, and ε is defined as the parameter of the stopping criterion, in which the value is taken between zero and one. Thus, the value of the variables ε, n_s and n_a is randomly generated.

ii) To estimate the radius of the enclosing ball in the spherical SVM classifier (Strack *et al.*, 2013) , the radius calculation is given as

$$\hat{R} = \sqrt{\psi + 1 + \frac{1}{C}} \tag{15}$$

where $\hat{R}$ is the radius of the enclosed ball and ψ is defined as the square norm of the input vector.

iii) If $W_i \neq 0$, then the vectors X_i lie on the border of the enclosing ball. If the vectors lie inside the ball, then they are considered as non-support vectors. This approach uses two types of violators $\tilde{v}_a$ and $\tilde{v}_b$. These violating vectors have non-zero weights. One vector lies outside of the enclosing ball, and another one lies inside the ball. If the distance among the violating vector $\tilde{v}_a$ and cluster centre C is greater than the value of $(1+\hat{\varepsilon})\hat{R}$, then the vector $\tilde{v}_a$ is taken as farthest violating vector. Otherwise the difference between the cluster centre and input vector should be greater than $(1+\hat{\varepsilon})\hat{R}$ which can be given as follows:

$$\|C - \tilde{x}_i\| > \left(1 + \hat{\varepsilon}\right)\hat{R} \tag{16}$$

The centre C is shifted along with the two violating vectors $\tilde{v}_b - \tilde{v}_a$ to the new cluster centre C'(Strack *et al.,* 2013). After the new cluster centre is formed, the violating vector $\tilde{v}_b$ becomes the support vector. The computed radius of the enclosed ball will not alter; even the new cluster centre is generated. Thus, the calculation of the new cluster centre is represented by

$$C' = C - \mu(\tilde{v}_b - \tilde{v}_a) \tag{17}$$

iv) The violating vector $\tilde{v}_b$ which corresponds to the farthest vector from the enclosed ball and another violating vector $\tilde{v}_a$ corresponds to the closest support vector to the cluster centre. To find the new radius between the new cluster centre and vector $\tilde{v}_b$, it is expressed by$\hat{R} = \|C' - \tilde{v}_b\|$. The radius can be evaluated by

$$\|C - \mu(\tilde{v}_b - \tilde{v}_a) - \tilde{v}_b\|^2 = \hat{R}^2 \tag{18}$$

Here, the proposed multi-kernel function k is used, which consists of three kernel functions, that is, logarithmic, tangential, and exponential functions. Generally, the spherical SVM classifier contains only one kernel function. However, the drawback of single kernel function is that we can utilize this function in single characteristic of the image, but the images are represented by certain visual characteristics, such as shape, colour, and texture. To significantly enhance the classification accuracy, the multi-kernel function (MKF) is proposed in this paper. The kernel function is used to return the value from linearity to non-linearity, which is represented as dot products between the two arguments in the image. Thus, the multi-kernel function is applied between the violating vectors and cluster centre.

$$\hat{\mu} = \lambda - \sqrt{\lambda^2 - \frac{k(-\tilde{v}_b.*C) - \hat{R}^2}{k(-\tilde{v}_b.*C)}} \tag{19}$$

where k is the novel multi-kernel function consisting of the logarithmic, exponential, and tangential kernel functions. This multi-kernel function is represented as dot product between the violating vector and cluster centre, C. Mapping of the training data samples into high-dimensional data is done by the kernel function. The logarithmic kernel function contains only conditionally positive definite. The tangential function is equal to two layers perceptron neural network. The exponential kernel is interrelated with the Gaussian function but only with the Euclidean distance. This function is used to determine the weighting coefficients for each kernel (logarithmic, exponential, and tangential) rather than optimizing the kernel parameters of a single kernel.

v) Based on the two violating vectors $\tilde{v}_a$ and $\tilde{v}_b$ and the cluster centre C, the value λ can be calculated by

$$\lambda = \frac{(\tilde{v}_b - \tilde{v}_a)(\tilde{v}_b - C)}{k(-\tilde{v}_b.*C)} \tag{20}$$

Finally, the multi-kernel based spherical SVM classification algorithm searches the violating vector, which is placed farther than $(1+\hat{\varepsilon})\hat{S}$ from the cluster centre C. Then, the value of $\hat{\varepsilon}$ is initialized to 0.5 and gradually reduced to ε. Then, this process is continued until the value of $\hat{\varepsilon}$ is less than ε. Finally, based on the value μ and ε, the centre of the ball is updated.

5. RESULT AND DISCUSSION

This section demonstrates the experimental results and comparative performance analysis of the proposed face recognition system with the existing systems.

5.1 Experimental Results

The proposed multi-kernel based SIFT feature and spherical SVM classifier for face recognition are implemented using MATLAB. The obtained experimental results are explained below.

i) Dataset Description: The dataset for our proposed system consists of a number of individual face images, which are used for the experimentation and comparative performance analysis. Totally, the samples of 114 individual face images are available in the CVL database with seven different spatial locations for each person. In this paper, four samples of input images are collected from the CVL Face Database (CVL, 1999) for further evaluation.

ii) Evaluation metrics: The performances of our proposed system are analyzed for face recognition by using the parameters, such as FAR, FRR, and Accuracy. Then, the performance is compared with the existing systems, like HOG, SIFT, and WHOG.

iii) Methods taken for performance comparison:

HOG: The Histogram of Oriented Gradient descriptors (Chen *et al.,* 2014) is the feature descriptor for face recognition. The HOG descriptor is implemented by dividing the image into small connected regions, called grids. In each grid, the histogram of gradient directions or edge orientations is computed for the pixels. Then, the normalization is done by calculating the measure of the intensity through a large region of the image, known as bins. This histogram combination indicates the descriptors.

SIFT: The transformation of the image data into scale variant coordinates corresponding to the local features is done by the SIFT (Lenc & Král, 2015) feature. This method has a significant aspect to generate the large number of features with the entire range of scales and locations. It has four steps to extract the facial features, such as extrema detection, key point localization, orientation assignment, and descriptor calculation.

WHOG: This technique (Singh et *al.,* 2015) counts the occurrences of gradient orientation in a localized portion of the image. The distribution of intensity gradients or edge direction is used to describe the appearance and shape of the local object within an image. Initially, the image is divided into cells. Then, the magnitude and orientation are computed in each cell along with the weighted function. The weight function is determined by the summation of the magnitude of all cells.

KSIFT: The proposed kernel based SIFT feature is used to extract the facial features for the better recognition. Initially, the SIFT features are extracted from a reference image set and then stored in the database. The key point descriptors are the highly distinctive stage that permits to match a single feature with the database. Thus, instead of the Gaussian kernel in SIFT feature, we propose the multiple kernel function for the descriptor calculation stage.

iv) Experimental Results:

The experimental results of the proposed KSIFT feature are shown below. The input image is pre-processed and then given to the KSIFT to extract the facial feature. Figure 4 demonstrates the experimental results. In figure 4, the input face images of four persons are taken from the database, and then, the KSIFT features are extracted from the input image.

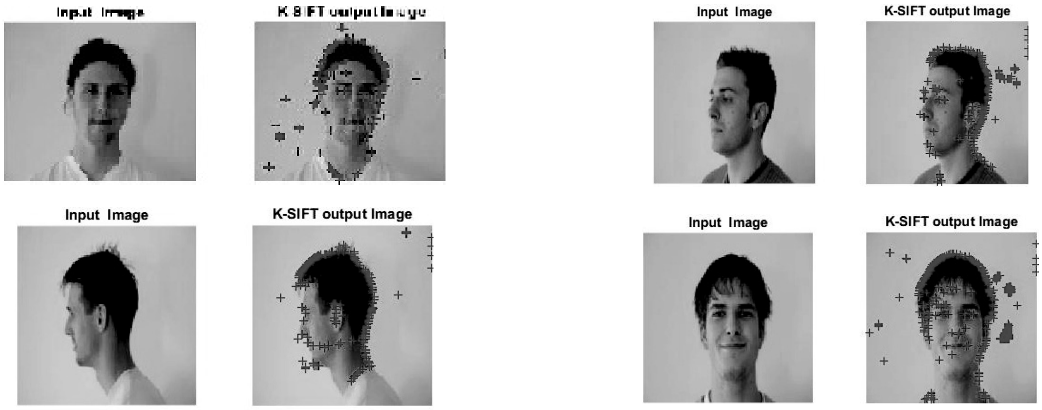


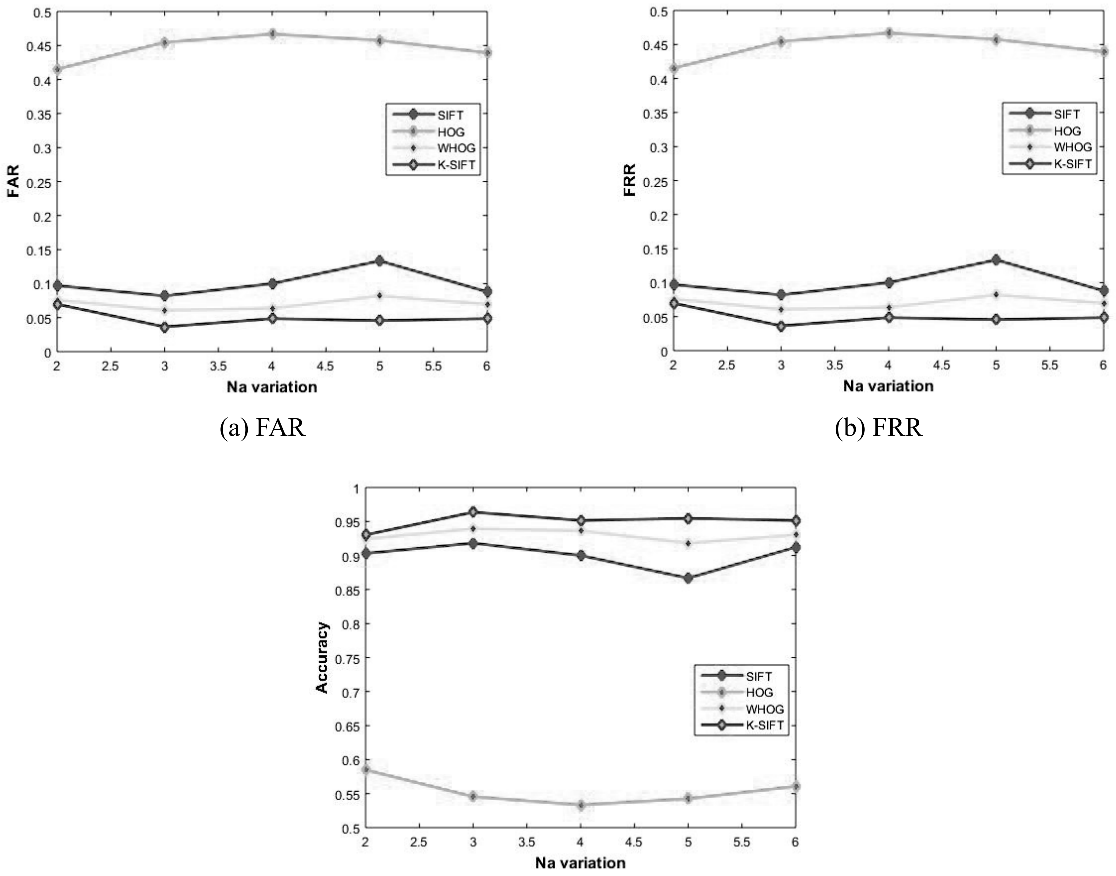
Fig. 4. Input images and KSIFT feature images.

5.2 Performance analysis

In this section, the comparative performance analysis of the face recognition system is described. The performance of the proposed multi-kernel based SIFT feature and spherical SVM classifier is analyzed by the parameters, such as false acceptance rate, false rejection rate, and accuracy. Then, the analyzed performance is compared with some existing methods, such as HOG, SIFT, and WHOG.

a) Analysis by n_a

The performance is analyzed using the number of draw attempt variations for the FAR, FRR and accuracy, which is shown in figure 5. False acceptance rate is the measure that an identity is a legitimate one while, in reality, it is an imposter. Thus, the frequency at the false accept error is called false acceptance rate. The performance of FAR rate is analyzed, which is shown in figure 5.a. When the number of draw attempt is three, the existing method like HOG attains the higher false rate of 45%. But our proposed method achieves only 4% of false acceptance rate. While varying the number of draw attempts, the false acceptance rate of our proposed method is also reduced gradually when compared with the HOG, SIFT, and WHOG and it is shown in figure 5.a. Then, another metric is FRR that is defined as the measure that an identity is not a legitimate one belonging to the corresponding person. The frequency at the false reject error is called false rejection rate (FRR). The figure 5.b demonstrates the performance trade-off between the FRR and number of draw attempts. The maximum FRR value is obtained in the existing HOG method, then the SIFT feature contains 10% of false rejects rate and weighted HOG method achieves 7.5%. When compared with these existing methods, our proposed method is utilized to enhance the better accuracy value by attaining the very low false reject rate of 3%. The most significant parameter for recognition is accuracy. The accuracy is defined by the degree of measurement, which provides the standard value for better recognition. Due to the maximum value of FAR and FRR, the existing HOG method attains only the 5.5% of accuracy. However, figure 5.c depicts that our proposed multi-kernel method ensures the better recognition rate by obtaining the higher accuracy of 96% which is high when compared with the HOG, SIFT, and weighted HOG method.



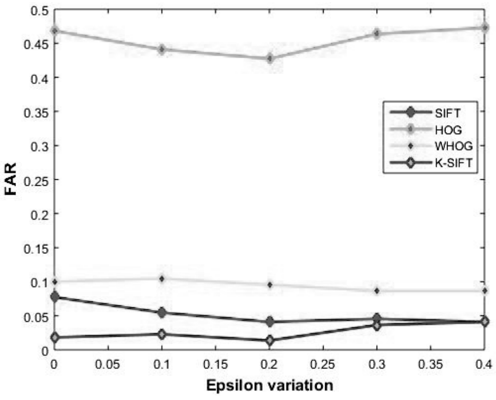
(a) FAR (b) FRR

(c) Accuracy

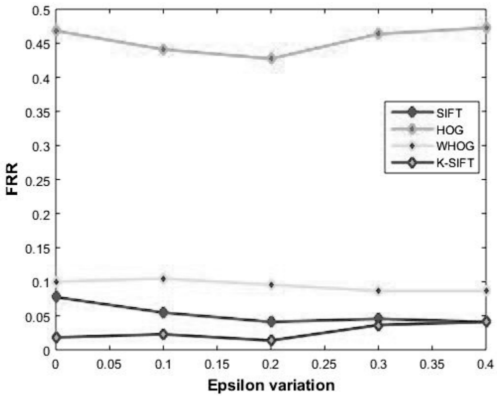
Fig. 5. Performance analysis by the number of draw attempts.

b) Analysis by epsilon (ε)

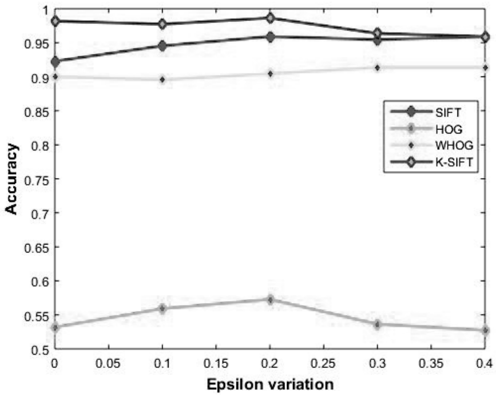
The epsilon is defined in the spherical SVM classifier for the stopping criterion. The performance is analyzed using the epsilon variation for the parameter FAR, FRR, and accuracy, which is demonstrated in figure 6. Figure 6.a shows the FAR performance analysis. But the value of epsilon ranges between zero and one. So, when the stopping criteria are 0.2, the SIFT feature method has 5% false acceptance rate. Then, 10% of false accept rate is obtained by the weighted HOG method. But figure 6.a proves that our proposed KSIFT method attains the minimal value when compared with the existing systems. Then, the false rejection rate performance is demonstrated in figure 6.b. The weighted HOG method sustains the same 10% false reject rate value while varying the epsilon. The FRR value is moderately reduced in the proposed KSIFT method. Thus, compared to the existing method, the minimum false value is acquired, which is depicted in figure 6.b. The better performance for recognition is determined by the accuracy value. Initially, the proposed system achieves the higher accuracy value 96% when compared to the existing systems. Among the existing systems, the histogram of oriented gradient method attains the very low accuracy value. Figure 6.c shows that the proposed system ensures the better accuracy performance for face recognition when compared to the HOG, SIFT feature, and weighted HOG method.



(a) FAR



(b) FRR



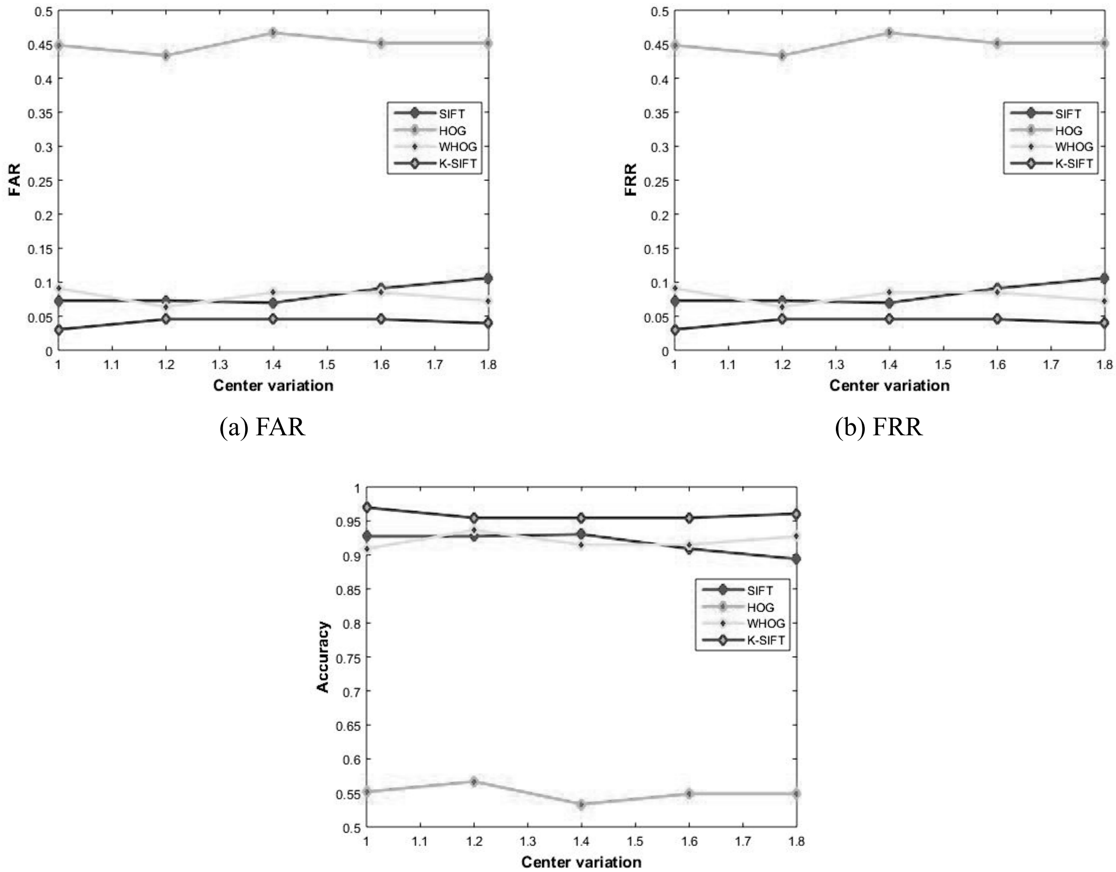
(c) Accuracy

Fig. 6. Performance analysis by stopping criterion (ε).

c) Analysis by cluster centre, C

The cluster centre is employed for the multi-kernel based spherical SVM classifier. Then, the new cluster is generated by the two violating vectors. Thus, the performance of FAR, FRR, and accuracy using the cluster centre variation is depicted in figure 7. The FAR is defined as the percentage of invalid inputs, which are incorrectly accepted. The false acceptance rate is shown in figure 7.a. The existing scale invariant feature transform (SIFT) method obtains the false accept value of 7% and then is gradually increased by varying the cluster centre. Then, it leads to mitigate the performance for recognition. The proposed KSIFT method achieves 4% false accept rate significantly when compared to the existing systems. The FRR metric is defined by the percentage of valid inputs, which are incorrectly rejected. Figure 7.b shows the trade-off between FRR and cluster centre. When the cluster centre is 1.2, the existing methods like HOG contain 44% of FRR value, SIFT feature has 7.5% FRR value, and 6.5% FRR is achieved by WHOG.

Then, the proposed method is compared with the existing systems in figure 7.b, which depicts that the FRR value is greatly mitigated in the KSIFT method. The metric accuracy is used to improve the classification accuracy for better recognition rate. Figure 7.c demonstrates the comparative analysis of accuracy value. When the cluster centre is 1.6, 55% accuracy value is acquired by HOG. The SIFT method has 90% accuracy, and the WHOG method achieved 91%. The proposed KSIFT method provides the better accuracy rate when compared with the existing systems, which is illustrated in figure 7.c.



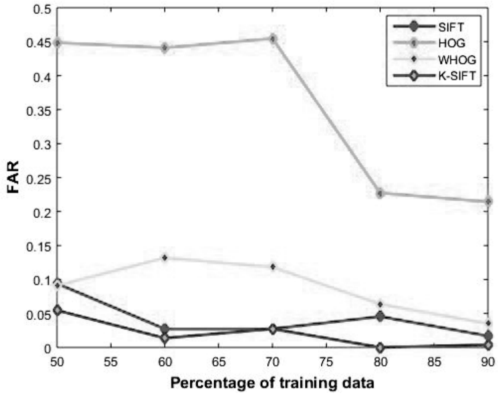
(a) FAR (b) FRR

(c) Accuracy

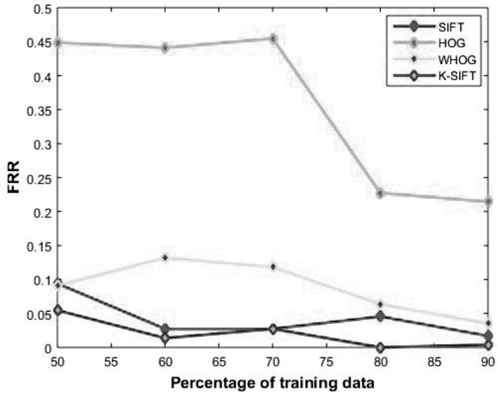
Fig. 7. Performance analysis by cluster centre.

d) Analysis by percentage of training data

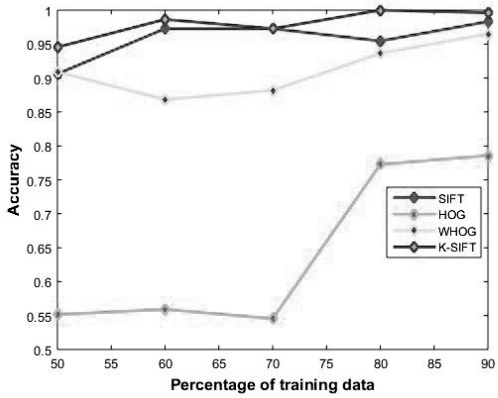
The performances of FAR, FRR, and accuracy are demonstrated in figure 8. Some of the training data is used to classify the features by the spherical SVM classifier in training phase. Then, the rest of the data are fed into the classifier during testing phase for recognizing the corresponding person by their faces. When the percentage of training data is 60, the HOG method attains 45% FAR value. Then, the weighted HOG system achieves 12.5% false accept value and SIFT method has 4% value. In figure 8.a, the proposed system achieves 3% false value, which is then gradually reduced by varying the percentage of training data. FRR estimates the probability that a system rejects a corresponding person incorrectly as a negative match. The FRR performance is analyzed in figure 8.b. For 70% of training data, the existing methods, such as HOG, SIFT, and WHOG, achieve the FRR value of 45%, 12%, and 4%, respectively. Compared with the existing systems, the proposed method exploits 3% false reject rate and then it is moderately reduced, which is shown in figure 8.b. The accuracy metric provides the true value for the face recognition systems. Figure 8.c shows the analyzed performance of accuracy value. While increasing the training data samples from 70 to 80%, the accuracy value is also greatly increased for all the methods. But the proposed KSIFT method attains the maximum accuracy value when compared with the existing system like HOG, SIFT feature, and weighted HOG method. Finally, we infer from figure 8.c that the higher accuracy of 99% is acquired by the proposed kernel based SIFT method, which gives the better performance recognition rate.



(a) FAR



(b) FRR



(c) Accuracy

Fig. 8. Performance analysis by the percentage of the training data.

5.3 Comparative Discussion

Here, the comparative discussion of the proposed method with the existing methods, SIFT, HOG, and WHOG is described. Table 1 shows the comparative discussion of the proposed method with the existing methods, such as SIFT, HOG, and WHOG. When the performance is analyzed by the number of draw attempt variations, the FAR of the existing methods, such as SIFT, HOG, and WHOG is 0818, 0.4152, and 0.0606, respectively, while the FAR of the proposed K-SIFT is 0.0364. Similarly, the proposed method has the minimum FAR than the existing methods while analyzing the performance using epsilon variation and cluster centre variation. The FRR of the proposed K-SIFT is 0.0364 and the FRR of the existing methods, that is, SIFT, HOG, and WHOG, is 0.0818, 0.4152, and 0.0606, respectively, while the performance is analyzed by the number of draw attempt variations. Similarly, the proposed method has the minimum FRR than the existing methods when the performance is analyzed by the epsilon variation and the cluster centre variation. When the performance is analyzed by the cluster centre variation, the accuracy attained by the proposed K-SIFT method is 0.9697 while the existing methods, such as, SIFT, HOG, and WHOG, attain the accuracy of 0.9303, 0.5667, and 0.9364, respectively. Similarly, the proposed method has the maximum accuracy than the existing methods when the performance is analyzed by the number of draw attempt variations and epsilon variation. From table 1, it can be concluded that the proposed method has the better performance than the existing methods, such as SIFT, HOG, and WHOG.

Table 1: Comparative Discussion of the proposed method with the existing methods, such as SIFT, HOG, and WHOG.

	Analysis by n_d			Analysis by epsilon (ε)			Analysis by cluster centre, C		
	FAR	FRR	Accuracy	FAR	FRR	Accuracy	FAR	FRR	Accuracy
SIFT	0.0818	0.0818	0.9182	0.0409	0.0409	0.9591	0.0697	0.0697	0.9303
HOG	0.4152	0.4152	0.5848	0.4273	0.4273	0.5727	0.4333	0.4333	0.5667
WHOG	0.0606	0.0606	0.9394	0.0864	0.0864	0.9136	0.0636	0.0636	0.9364
K-SIFT	0.0364	0.0364	0.9636	0.0136	0.0136	0.9864	0.0303	0.0303	0.9697

6. CONCLUSION

This paper proposes the kernel based Scale Invariant Feature Transform (KSIFT) and spherical SVM classifier for face recognition. Here, various individual face images are utilized for the face recognition system and different kernel functions are used to develop a new multiple kernel function (MKF). The input face images are pre-processed to obtain a suitable image for further steps. Then, the features are extracted by the proposed kernel based SIFT feature. The extrema detection, removal of key points, orientation assignment, and descriptor calculation are the four stages in SIFT feature. The proposed multiple kernel function is utilized in the descriptor calculation instead of Gaussian kernel function, which is named as KSIFT feature. After facial features are extracted, the features are classified using the multi-kernel based spherical SVM classifier. Finally, the experimental results are estimated, and the comparative performance is analyzed with the existing system using the metrics, such as FAR, FRR, and accuracy. The proposed method attains the accuracy of 99%, which is higher than the existing methods, and it ensures better face recognition performance.

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تحويل السمات غير المتأثرة بمقياس المرتكزة على النواة ومصنف SVM الكروي للتعرف على الوجه

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الخلاصة

نظراً لتوافر نطاق واسع من التطبيقات التجارية والقانونية والتقنيات العملية، اكتسب التعرف على الوجوه اهتماماً كبيراً بين الباحثين مؤخراً. وتقدم المؤلفات البحثية أنظمة عديدة للتعرف على الوجوه قادرة على قياس ومطابقة السمات المميزة المُعدة لتحديد هوية شخص أو التحقق منها من صورة رقمية. ويطرح تحديد السمات المميزة من صورة الوجه جوانب مختلفة من التحديات بسبب الأوضاع المختلفة وظروف الإضاءة. وللتغلب على هذه التحديات الكبيرة في الطرق الحالية، يقترح هذا البحث خوارزمية لتحويل السمات غير المتأثرة بمقياس والمرتكزة على النواة ومصنف SVM الكروي للتعرف على الوجوه. علاوة على ذلك، تم تقديم دالة weightage جديدة لاستخراج السمات وتصنيفها، والتي تسمى دالة النواة المتعددة (MKF). ولاستخراج ملامح الوجه، اعتمدنا تقنية SIFT، والتي تم تعديلها في مرحلة الواصف بواسطة دالة الحمل MKF المُقترحة، وبالتالي قمنا بتطوير تقنية جديدة أطلقنا عليها اسم KSIFT. تم استخدام مصنف SVM متعدد النواة لأغراض التصنيف. وقمنا بتحليل أداء الطريقة المقترحة من خلال إجراء تجربة على قاعدة بيانات CVL Face من حيث مقاييس التقييم، مثل: FAR وFRR والدقة. وبعد ذلك، قمنا بمقارنة الأداء مع الأنظمة الحالية، مثل: HOG، SIFT وWHOG. ومن النتائج التجريبية، اتضح أن الطريقة المقترحة قد حصلت على أعلى دقة بنسبة ٩٩٪ لنظام التعرف على الوجوه.