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## SYMBOLIC REPRESENTATION OF EDGE LET FEATURES FOR FACE RECOGNITION: A NOVEL APPROACH.

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### ABSTRACT

This paper presents a new approach aimed to design a symbolic face recognition system. Edge let features for face recognition are proposed in the paper, are incorporated in the feature vector used to design the pattern recognition system. Edge let feature lines are considered as new features based on previous studies related to face recognition tasks. An identification scheme of the objects based on the proposed representation model and features extraction is designed. The performance of the proposed face recognition system turns out to be 92% of correct classification tested on the ORL and Yale databases..

**Keywords:** Face recognition, interval valued representation..

### 1. INTRODUCTION

Face detection is a fundamental problem in Image processing, Computer Vision and pattern recognition, and it is an indispensable technology in emerging applications such as information security, aadhaar card, smart cards, entertainment, law enforcement, human computer interaction and video surveillance, content based image retrieval and driver assistance. Lots of researchers have paid much attention to face detection and proposed many powerful features and discriminative algorithms. Although great advances have been made for face detection, it is still a challenging problem to design a reliable face detection in images. One of the most important reasons is that the appearances of different face change dramatically due to viewpoints, illuminations, deformations and occlusions. To overcome the large variance in appearance, all kinds of cues, such as shape, color and texture, are extracted from images of face detection. Among these cues, shape is considered as one of the most discriminative and reliable one. Therefore, lots of features are proposed to describe shape characteristics for face detection.

Designing efficient features based on shape cue faces two challenging problems. First, the shapes of one face class have large intraclass variance due to many factors, such as translation variance, scale variance, and deformation. We extract the edge maps of the side-view faces and average the edge magnitudes. Apparently, the edge maps cannot be well aligned since there are different structures and different translations and scales for different face images. As a result, it is difficult to find a shape-guided feature that is well aligned with the edges of all the faces. Second, there seems to be a contradiction between discriminability and computation cost of features. Significant shape features are HOG and CoHOG usually have high computation costs, which will slow down the detection process. On the dissimilar, most of the fast features may be not robust or discriminative for describing faces with complex shapes. For example, Haar-like features are short of discriminability as they describe shapes with simple contrast patterns in rectangular regions. Therefore, it is a challenging problem to design such a feature that has dominant discriminability and low computation cost.

Although the shapes of a specific class have large intra class variance, some basic shape elements are relatively stable. We can find many consistent shape elements on the mouth, nose, eyes, and chin. We highlight some of these face structures.

Based on these observation, we propose a novel method for face recognition. In our method, the local occlusion and pose variation in face detection, face can be looked on as a whole composed of several parts from up to down. Initially, the face is divided into a number of local regions and various features are extracted from them. Every region is identified by a local classifier and the identified region is assigned a preliminary part label. A random field is established based on these labels and multiple dependencies between different part are modeled in a CRF framework.

In this research article a new methodology meant to design a symbolic face recognition system. Face feature edge let feature are considered in the paper, are joined in the feature vector used to structure the face recognition system. Face feature lines are considered as new features dependent on past studies related to face recognition tasks on babies. A plan of ID of the items based on the proposed feature extraction and representations model is likewise designed.



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The composition of the paper is as follows. In area 2 a brief writing survey is presented. In area 3 we present the proposed model for object recognition in infrared pictures. Area 4 talks about experimentation and relative analysis performed on the proposed models. Paper will be closed in area 5.

### 2. LITERATURE SURVEY

Generally, the two-dimensional image feature extraction methods in image representation could be broadly summarized into two categories based on their properties, i.e., holistic methods and local methods. The holistic methods generally extract features from a facial image by treating the image as a whole. Principal component analysis (PCA) [1], linear discrimination analysis (LDA) [2], independent component analysis (ICA) [3], locality preserving projection (LPP) [4], local linear embedding (LLE) [5], local discriminant embedding (LDE) [6], marginal Fisher analysis (MFA) [7], discriminant simplex analysis (DSA) [8], nonnegative graph embedding (NGE) [9], clustering-guided sparse structural learning (CGSSL) [10] and robust structured subspace learning (RSSL) [11] are the typical ones of this kind. These methods are liable to be influenced by face image pose, illumination, scale and so on, and variations in these factors can largely degrade its recognition performance.

The local methods usually consider several regions or sets of isolated points, from which features for classification are extracted. Classical methods such as local binary pattern (LBP) [12,13], scaleinvariant feature transform (SIFT) [14,15], speeded-up robust features (SURF) [16], weber local descriptor (WLD) [17], Weber local binary pattern (WLBP) [18], monogenic binary coding (MBC) [19], histograms of local dominant orientation (HLDO) [20], enhanced local directional pattern (ELDP) [21], farthest point distance (FPD) descriptor [22], rotation-invariant fast feature (RIFF) [23], edge orientation difference histogram (EODH) [24] have been widely examined. Compared with holistic methods, local methods are distinctive and invariant to many kinds of geometric and photometric transformations, and have been gaining more and more attention because of their promising performance.

Being one of the representative local image descriptors, local binary pattern (LBP) was first introduced by Ojala et al. [12], and it has shown a high discriminative ability for texture classification due to its invariance to monotonic gray level changes. Afterwards, many variants of LBP have been introduced to further improve its performance. However, the feature of all these methods being coded into the bit-string is prone to change due to noise or other variations.

Considering that Kirsch compass mask enhances the useful information like edge texture and meanwhile suppresses the external noise effect, recently it has been widely used for image feature extraction. Jabid et al. [25] proposed local directional patterns (LDP), which is an eight-bit binary code calculated by first comparing the absolute edge response values derived from different directional Kirsch masks. Then the top k prominent values are selected and the corresponding directional bits are set to 1, the remaining (8-k) bits are set to 0. Finally, convert the binary number into a decimal one, and the decimal value is the corresponding image pixel LDP expression. Zhong and Zhang [26] proposed the enhanced local directional patterns (ELDP), which improved the LDP in the following two aspects. First, take the sign of the Kirsch edge response into consideration, which means two opposite trends (ascending or descending) of the gradient and contain some more discriminant information. Second, only the most and the second most prominent edge response directions are take into the local pattern coding. Kang et al. [27] proposed the structured local binary kirsch pattern (SLBKP), which quantify the eight edge responses into two four-bit binary codes according to the predefined threshold. Castillo et al. [28] proposed local sign directional pattern (LSDP), similar to the ELDP, the only difference is that it codes the most and the least prominent edge response directions. Rivera et al. [29,30] proposed local directional texture pattern (LDTP), which is the mixture coding of direction number of local most prominent Kirsch mask edge response and intensity differences along two greatest edge responses directions.

### 3. PROPOSED METHODOLOGY

#### Edge Based Approaches

This strategy utilizes the edge map of the picture and distinguishes the images in the picture terms of edges. Considering edges as features is advantageous on account of numerous reasons, as they are to a great extent invariant to illumination conditions and varieties in objects colors and textures. They likewise speak to limits of the question well and speak to the data efficiently in the vast spatial degree of the pictures. The main two



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deviations in these strategies are: utilization of the complete contour (shape) of the object as the feature and utilization of collection of contour fragments as the element of the object.

Hamsici the whole shape of the contour of the edges to get a foothold in the recognition of a set of points of contact between them. Schindler thought about the super-pixels, such as segmentation based methodologies. They are viewed as close to the contours of the surrounding territories from the beginning point to get the contours of the closure. Ferrari at the edges of the object detection offers the best of contemporary techniques utilized in the most advanced edge detection method. After the closure of the contours of the edges to frame a network connected over the small gap between them. Ren is significantly more difficult because of the presence of background information in the natural pictures; the contours of the object are utilized to finish a triangulation. All these strategies require additional computation intensive treatment and are often sensitive to the decision of an assortment of practical outlining parameters of note. The other issue with such a feature for testing and approval of pictures, is available to match the contours of even a deficient picture and consequently the whole contour of the degree is commonly low.

### Patch Based Approach

The patch based feature extraction approach has been being used since over two decades, and edge-based features are generally new in compared patch based method. Moravec considered nearby maxima of least intensity gradients, he called it as corners and chose a patch around these corners. This work is enhanced by Harris, which made the new detector less delicate to noise, edges and an isotropic nature of the corners proposed. In its ordinary form, the features of the object templates so as to utilize a similar size of a rectangular or square in local areas. Such features are effective for multi-scaling (the appearance of a variety of material). The following may not be reasonable because of the size of the fixed patch. The size of the patch is little; it is enormous yet may not cover the most important local feature. Such a feature is a short list of data might be lost. The size of the patch is huge then again, it may not be available at the same time with different pictures or in excess of one separate cover. Another short coming of numerous little rectangular patches should be defeated so as to assess the attributes and the material. Both of these are computationally costly and memory intensive. The pictures have a variety of features, for example, robustness, utilization of littler or bigger features, better and quicker learning abilities, and requiring less storage.

### Edgelet Features

Bo wu et al (2005) has introduced the edge let feature, which are the short segments of human contour. An edgelet feature can be defined in the form of a line, arc, semi-circle, and symmetric pair. The position  $w$  in the edge intensity  $M^I(w)$  and normal at position  $w$ ,  $N^I(w)$  an affinity is estimated. It is calculated between the edgelet and image  $I$  at the position  $w$  and is defined;

$$A(W) = (1/t) \sum_{i=1}^t \left[ |M^I(p_{i+w}) - N^I(p_{i+w}, n_i^e)| \right]$$

Where  $\{p_i\}_{i=1}^t$  is the position of an edgelet and  $\{n_i^e\}_{i=1}^t$  is the vector of the points in a given edgelet,  $t$  is the length of the edgelet.  $M^I(w)$  and  $N^I(w)$  are calculated by  $3 \times 3$  sobel kernel convolution, and are used for the quantization of the normal vectors into the discrete values. In this paper

In this article an interval valued representation of features for ID of faces in the pictures is displayed. The proposed model can be separated into various stages like interval valued representation stage and face recognition organize.

### Interval valued Representation of Features

The proposed representation model depends on representing an object by edge let features of the pictures of a class in the form of symbolic data. An edge let is a feature which is a short line segment or a curve present in the picture which distinguishes the positions and typical vectors of the points in an edge by  $\{U_i\}_{i=1}^k$  and  $\{n_i^E\}_{i=1}^k$ ,  $k$  is the length of the edge let. Given an input picture  $I$ , denoted by  $M^I(p)$  and  $n^I(p)$  are the intensities of edge at position  $P$  of input picture  $I$ . In practice, edge orientations are quantized and represented by  $\{V_i^E\}_{i=1}^k$  and  $V^I(p)$  of the input picture  $I$  respectively. Features samples of an objects of a specific class experiences intra class variations. A viable feature representation for capturing the varieties of feature samples through their assimilation by the utilization of interval valued representation called as symbolic feature vector is proposed.

Let  $[Sp_1, Sp_2, Sp_3, \dots, Sp_n]$  be the set of  $n$  samples of class  $D_j$ ,  $j = 1, 2, 3, \dots, N$  ( $N$  denotes the number of classes(domains)) and let  $F_{pi} = [f_{pi1}, f_{pi2}, f_{pi3}, \dots, f_{pim}]$  be the  $m$  edgelet features of  $Sp_i$  of class  $C_{dj}$ . The  $\mu_{jk}$ ,  $k = 1, 2, \dots, m$  be the mean of  $k$ th features and can be obtained from the following equation

$$\mu_{jk} = 1/n \sum_{i=1}^n [f_{pik}]$$

Standard deviation of the  $k$ th feature and it is calculated using the following equation.

$$\sigma_{jk} = [1/n \sum_{i=1}^n [(f_{ik} - \mu_{jk})^2]]^{(1/2)}$$



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Now standard and mean deviation are considered in the identification of the intra class variations in  $k$ th feature space of the  $j$ th class and it is represented by interval valued feature representation as  $[f_{jk}^-, f_{jk}^+]$  where

$f_{jk}^+ = \mu_{jk} + \sigma_{jk}$  and  $f_{jk}^- = \mu_{jk} - \sigma_{jk}$

Now, these interval valued representation of the reference image of class  $C_j$  will be created by representing each in feature ( $k=1,2,3, \dots, m$ )

$\{[f_{j1}^-, f_{j1}^+], [f_{j2}^-, f_{j2}^+], [f_{j3}^-, f_{j3}^+], \dots, [f_{jm}^-, f_{jm}^+]\}$

Face Recognition Stage

Face recognition displayed in this work considers a query picture which is depicted by the set of  $m$  fresh features, as they are the features of one sample of test picture and are compared and the representative feature of the particular classes introduced in the knowledgebase. Since the features are changed into interval valued representation, the proposed model definitely diminishes the feature space which in turn limits the computational time for object recognition in the infrared pictures. So from this we can see that the proposed edgelet features with interval valued out plays out the state art techniques.

Let  $F_{test} = [ft_1, ft_2, ft_3, \dots, ft_m]$  be the  $m$ -dimensional crisp features relating to an query picture. Amid the object recognition, each  $k$ th feature value of the test picture will be compared with the relating interval valued feature and inspected whether the feature value of the test picture exists in the corresponding interval. The quantity of features of a test picture which fall inside the corresponding interval of the separate class will give the level of closeness

$\dots$  Similarity (Test, Training) =  $\sum_{k=1}^m Sim(f_{tk}, [f_{jk}^-, f_{jk}^+])$

Here  $[f_{jk}^-, f_{jk}^+]$  represents the  $k$ th feature interval of the  $j$ th class and it is defined as

Similarity (Test, Training) =  $f(x) = \begin{cases} 1, & \text{if } (f_{tk} \geq f_{jk}^- \text{ and } f_{tk} \leq f_{jk}^+) \\ 0, & \text{otherwise} \end{cases}$

$$Similarity (Test, Training) = f(x) = \begin{cases} 1, & \text{if } (f_{tk} \geq f_{jk}^- \text{ and } f_{tk} \leq f_{jk}^+) \\ 0, & \text{otherwise} \end{cases}$$

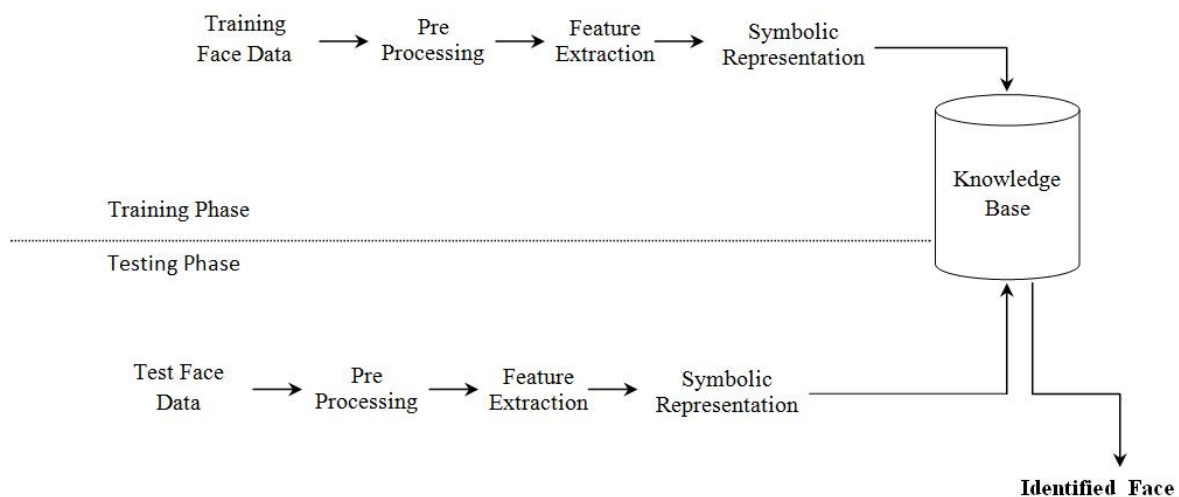


Figure 1 Block Diagram of the Proposed Approach.

### 4. EXPERIMENTAL SETUP

This area introduces the details of the experiments conducted to represent the viability of the proposed technique on publically accessible corpuses. Two sets of experimentations are conducted where each set contains three distinct trails. In the first set of experiments, we have utilized 40% of the database for training and remaining 60 % is utilized for testing. In second set of experiments, we have utilized 60 % training and 40



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% for testing. In each trail we have randomly chosen training and testing tests. With the end goal of evaluation of the outcomes, we have calculated accuracy, recall and f-measure for each trail. The details of the tests are shown in the following table1.

**Table 1 : Result of the proposed method**

Datasets	40% : 60%			60% : 40%		
	Precision	Recall	f Measure	Precision	Recall	f Measure
ORL	0.7825	0.7955	0.7889	0.9154	0.9244	0.9199
Yaale	0.8115	0.8012	0.8063	0.8897	0.8871	0.8884

### 5. CONCLUSION

This article exhibits a novel technique for representing face pictures by the utilization of edgelet feature for face recognition applications. A strategy for identification of the face based on the proposed edgelet feature and interval valued representation is also proposed. Since the features are changed into interval valued representation, the proposed model radically decreases the dimension of the feature space which intern lessens the computational time for object recognition in the infrared pictures. The proposed algorithm is basically analyzed on publically accessible corpuses. Further a broad experimentation is led on publically accessible datasets. In any case, the main advantage of the proposed procedure is that it requires moderately a less time for identification as it depends on a straightforward matching strategy.

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