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COMBINATION OF FUZZY AND SYMBOLIC REPRESENTATION OF EDGE LET FEATURES FOR FACE RECOGNITION: A NOVEL INTEGRATED APPROACH Yogish Naik G R, Prabhakar C. J.

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Abstract

This paper presents a new combined Fuzzy and Symbolic Representation of EdgeLet Features for Face Recognitionsystem is presented. Face feature edge let features are proposed in the paper, are incorporated in the feature vector used to design the pattern recognition system. Face feature lines are considered as new features based on previous studies related to face recognition tasks on newborns. A scheme of identification of the objects based on the proposed features extraction and representation model is also designed. The performance of the face recognition system turned out to be 92% of correct classification tested on the ORL and Yale databases.

Introduction

Face recognition is one of the most interesting and challenging areas in computer vision and pattern recognition. Current face recognition systems have high recognition rates when face images are acquired in controlled conditions. However, robust face recognition systems are required in sophisticated security systems. Robustness must be translated into system tolerance to viewpoint, pose, illumination, and facial expression [1]-[16]. Two of the most important face recognition methods currently used are the eigenface and Fisherface methods. The eigenface method, or principal component analysis (PCA), is the most well known method for vector feature representation in face recognition [17]. PCA is a popular method in pattern recognition and communication theory that is quite often referred to as a Karhunen–Loeve transformation (KLT). The PCA approach exhibits optimality when it is applied to reduce the dimensionality of a feature vector [18]. The PCA method is used in this work to map an original feature vector to a new feature space.

In this researcharticle a new approach aimed to design a symbolic face recognition system. Face feature edge let features are considered in the paper, are incorporated in the feature vector used to design the face recognition system. Face feature lines are considered as new features based on previous studies related to face recognition tasks on newborns. A scheme of identification of the objects based on the proposed features extraction and representation model is also designed.

The rest of the paper is organized as follows. In section 2 a brief literature survey is presented. In section 3 we present the proposed model for object recognition in infrared images. Section 4 discusses about experimentation and comparative analysis performed on the proposed models. Paper will be concluded in section 5.

Literature Survey

This section presents adetailed literature survey of the feature extraction techniques for face recognition using edge let features are presented. Since this article focuses on the face recognition, we restrict our study tofeature extraction of conventional face recognition approaches.

In literature most of the works on feature extraction techniques are classified into two categories like edge-based type and patch based feature types. From the survey it is clear that some approaches use combination of edge-based type and patch based feature type [5-9].

Edge Based Approaches

This method uses the edge map of the image and identifies the objects in the image in terms of edges [5, 6, 10-11]. Considering edges as features is advantageous because of many reasons, as they are largely invariant to illumination conditions and variations in objects' colors and textures. They also represent boundaries of the object well and represent the data efficiently in the large spatial extent of the images [10]. The main two deviations in these techniques are s: use of the complete contour (shape) of the object as the feature [12-17] and

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use of collection of contour fragments as the feature of the object [5, 6,11, 18-24]. Figure 2 shows an example of complete contour and collection of contours for an image.

Hamsici [12] 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 [16] considered the super-pixels, such as segmentation based approaches. They are considered to be close to the contours of the surrounding areas from the very beginning to get the contours of the closure. Ferrari[21] at the edges of the object detection offers the best of contemporary methods used in the most advanced edge detection method. After the closure of the contours of the edges to form a network connected across the small gap between them. [19] Ren is significantly more difficult because of the presence of background information in the natural images; the contours of the objects are used to complete a triangulation. All of these techniques require additional computation intensive treatment and are often sensitive to the choice of a variety of practical outlining parameters of note. The other problem with such a feature for testing and validation of images, is available to match the contours of even an incomplete image and therefore the entire contour of the degree is generally low [15].

Patch Based Approach

The patch based feature extraction approach has been in use since more than two decades [25], and edge-based features relatively new in comparedpatch based technique. Moravec [25] considered local maxima of minimum intensitygradients, he called it as corners and selected a patch around these corners. This work isenhanced by Harris [26], which made the new detector less sensitive to noise, edges, andanisotropic nature of the corners proposed in [25]. In its regular form, such as the features of the object templates [27] in order to use the same 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 suitable due to the size of the fixed patch. The size of the patch is small, it is big but may not cover the most important local feature. Such a feature is a short list of information may be lost. The size of the patch is large on the other hand, it may not be present simultaneously with other images or more than one separate covers. Another shortcoming of many small rectangular patches needs to be overcome in order to assess the attributes and the material. Both of these are computationally expensive and memory intensive. The images have a variety of features such as robustness, use of smaller or larger features, better and faster learning capabilities, and requiring less storage [28].

Proposed Model

1. Introduction to Fuzzy THEORY

Fuzzy Theory Fuzzy logic in Fuzzy theory is in contrast with traditional Crisp logic, which only gets true or false for the question, which means it is limited in applying to the real world. There are three types of shapes taken by Fuzzy number used in Fuzzy Theory.

- 1. Bell-curve shape Bell-curve shape's graph's shape is smooth. Its fuzzy number's degree of membership
- 2. *Triangle shape* Triangle shape is a simplified version of Bell-curve shape, and is normally used. Its fuzzy number's degree of membership is μ tr (x).
- 3. *Trapezoid shape* Trapezoid shape is combination of Triangle shape and Bell curve's shape and its graph's shape is simple. Its fuzzy number's degree of membership $\mu tz (x)$ is. The membership function shows the closeness of x to r in a number from 0 to 1.

Shannon's Entropy Shannon's Entropy is a measure of uncertainty used in statistics, probability theory, computer science, and in statistical dynamics. It does a calculation with ratios, which means that even with different size of pictures, it wouldn't get bothered, which leads to higher accuracy on different sizes of images for facial recognition system. Shannon's entropy H(X) is

METHOD1 Fuzzy

- Calculate the length between two eyes, between end of nose and start of mouth, length between ears, length of mouth, length of eyebrow, and length from chin to middle of eyebrows, etc. All features are put to each set of features. (feature set: , ,)
- Draw face line until ears only for parts where is recognizable with computer. If size of input 1 and input 2 different, make the small one as large as the large input. And then, place lines in the same location in image. Subtract input 2 from input 1. Unless the area of result of subtraction is 0, =(leftover's



area)/(input 1's area). If leftover is 0, Subtract input 1 from input 2. If the area of the result is not 0, =(leftover's area)/(input 2's area). If leftover area is 0 again, =1. [7]

- Calculate each entropy for each feature sets to compare each features for each input. Since this is comparing features, this calculation will be crucial for the system.
- Calculate Bell-curve shape's fuzzy number's degree of membership $\mu A(x)$ for each feature sets. Since there are n feature sets, the calculation will be held for n times.
- Add up, and then divide the sum by n. Let's say the result of this is .Than, result of this algorithm, , which is similarity percentage of two inputs, will be like this:

2. Introduction to Symbolic Data

In this article an interval valued representation of features for identification of faces in the images is presented. The proposed model can be divided into different stages like interval valued representation stage and face recognition stage.

Interval valued Representation of Features

The proposed representation modelis based on representing an object by edgelet features of the images of a class in the form of symbolic data. An edgeletis a feature which is a short line segment or a curve present in the image which identifies the positions and normal 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 edgelet. Given an input image I, denoted by $M^I(p)$ and $n^I(p)$ are the intensities of edge at position P of input image I. In practice, edge orientations are quantized and represented by $\{V_i^E\}_{i=1}^k$ and $V^I(p)$ of the input image *I* respectively. Features samples of an objects of a particular class suffers from intraclass variations. An effective feature representation for capturing the variations of features samples through their assimilation by the use 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 $Fp_i = [fp_{i1,j}fp_{i2,j}fp_{i3,j}\dots, fp_{im}]$ be the m edgelet features of Sp_i of classCd_j. The μ jk, k = 1,2,...,m be the mean of k^{th} features and can be obtained from the following equation

$$\mu_{jk} = \frac{1}{n} \sum_{i=1}^{n} f p_{ik}$$

Standard deviation of the k^{th} feature and it is calculated using the following equation.

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

Now standard and mean deviation are considered in the identification of the intraclass 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 *Cdj* will be created by representing each in feature $(k=1,2,3,\ldots,m)$

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

Face Recognition Stage

Face recognition presented in this work considers a query image which is described by the set of m crisp features, as they are the features of one sample of test image and are compared with the symbolic feature of the respective classes presented in the knowledgebase. Since the features are transformed into interval valued representation, the proposed model drastically reduces the dimension of the feature space which inturnminimizes the computational time for object recognition in the infrared images. So from this we can notice that the proposed edgelet features with interval valued out performs the state art techniques.

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Let $F_{test} = [f_{tl}, f_{t2}, f_{t3}, \ldots, f_{tm}]$ be the m-dimensional crisp features corresponding to a query image. During the object recognition, each *k*th feature value of the test image will be compared with the corresponding interval valued feature and examined whether the feature value of the test image lies within the corresponding interval. The number of features of a test image which fall inside the corresponding interval of the respective class will give the degree of similarity.

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

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

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

Experimental Setup

To demonstrate the efficiency of the proposed algorithms, score level fusion method is adapted for the two different data representation techniques considered in the paper. Generally voting methods consider the *f*-measure values of the four different learning algorithms and predict the result which is selected by most classifiers. This can be helpful provided more than three output need to be fussed. Since in this article deals with four different methods need to be considered for fusion, a simple fusion method is formulated as follows *ClassificationScore* = $Max(Representation Model_1 + Representation Model_2)$

But for some applications, combination of classification algorithms plays a major role is assessing the performance of the model.



Fig.1. Proposed Fusion Based Approach

This section presents the details of the experiments conducted to represent the effectiveness of the proposed method on publically available corpuses. Two sets of experimentations are conducted where each set contains three different trails. In the first set of experiments, we have used 40% of the database for training and remaining 60% is used for testing. In second set of experiments, we have used 60% training and 40% for testing. In each trail we have randomly selected training and testing samples. For the purpose of evaluation of the results, we have calculated precision, recall and f-measure for each trail. The details of the experiments are shown in the following table1.



Table 1 : Kesuu oj ine proposea metnoas						
Datasets	40%:60%			60% : 40%		
	Precision	Recall	f Measure	Precision	Recall	f Measure
ORL	0.9256	0.9318	0.9287	0.9687	0.971	0.9698
Yaale	0.9198	0.9266	0.9232	0.9729	0.9765	0.9747

Conclusion

This article presents a novel method of representing face images by the use of edgelet features for face recognition applications. A method of identification of the face based on the proposed edgelet features and interval valued representation model is also proposed. Since the features are transformed into interval valued representation, the proposed model drastically reduces the dimension of the feature space which intern reduces the computational time for object recognition in the infrared images. The proposed algorithm is critically analyzed on publically available corpuses. Further an extensive experimentation is conducted on publically available datasets. However, the main advantage of the proposed technique is that it takes relatively a less time for identification as it depends on a simple matching strategy.

References

- [1] X. Lu, and A. K. Jain, "Deformation Analysis for 3D Face Matching", Proceedings of the Seventh IEEE Workshop on Applications of Computer Vision, 2005.
- [2] H. Cevikalp, M. Neamtu, M. Wilkes, A. Barkana, "Discriminative Common Vectors for Face Recognition", IEEE Transactions on Pattern Analysis and Machinery Intelligence, Vol. 27, No. 1, Jan 2005.
- [3] M. J. Er, W. Chen, S. Wu, "High-Speed Face Recognition Based on Discrete Cosine Transform and RBF Neural Networks", IEEE Transactions on Neural Networks, Vol. 16, No. 3, May 2005.
- [4] T. Kim, J. Kittler, "Locally Linear Discriminant Analysis for Multimodally Distributed Classes for Face Recognition with a Single Model Image", IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 27, No. 3, Marzo 2005.
- [5] Opelt, A. Pinz, and A. Zisserman, "Learning an alphabet of shape and appearance for multi-class object detection," International Journal of Computer Vision, vol. 80, pp. 16-44, 2008.
- [6] Z. Si, H. Gong, Y. N. Wu, and S. C. Zhu, "Learning mixed templates for object recognition," in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2009, pp. 272-279.
- [7] R. Fergus, P. Perona, and A. Zisserman, "A sparse object category model for efficient learning and exhaustive recognition," in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2005, pp. 380-387.
- [8] Y. Chen, L. Zhu, A. Yuille, and H. J. Zhang, "Unsupervised learning of probabilistic object models (POMs) for object classification, segmentation, and recognition using knowledge propagation," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 31, pp. 1747-1774, 2009.
- [9] J. Shotton, "Contour and texture for visual recognition of object categories," Doctoral of Philosphy, Queen's College, University of Cambridge, Cambridge, 2007.
- [10] J. Shotton, A. Blake, and R. Cipolla, "Multiscale categorical object recognition using contour fragments," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol.30, pp. 1270-1281, 2008.
- [11]I. A. Rizvi and B. K. Mohan, "Improving the Accuracy of Object Based Supervised Image Classification using Cloud Basis Function Neural Network for High Resolution Satellite Images," International Journal of Image Processing (IJIP), vol. 4, pp. 342-353, 2010.
- [12] O. C. Hamsici and A. M. Martinez, "Rotation invariant kernels and their application to shape analysis," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 31, pp. 1985-1999, 2009.
- [13] L. Szumilas and H. Wildenauer, "Spatial configuration of local shape features for discriminative object detection," in Lecture Notes in Computer Science vol. 5875, ed, 2009, pp. 22-33.
- [14] L. Szumilas, H. Wildenauer, and A. Hanbury, "Invariant shape matching for detection ofsemi-local image structures," in Lecture Notes in Computer Science vol. 5627, ed, 2009, pp. 551-562.
- [15] M. P. Kumar, P. H. S. Torr, and A. Zisserman, "OBJCUT: Efficient Segmentation Using Top-Down and Bottom-Up Cues," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 32, pp. 530-545, 2009.

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- [16] K. Schindler and D. Suter, "Object detection by global contour shape," Pattern Recognition, vol. 41, pp. 3736-3748, 2008.
- [17] N. Alajlan, M. S. Kamel, and G. H. Freeman, "Geometry-based image retrieval in binary image databases," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 30, pp. 1003-1013, 2008.
- [18] Y. N. Wu, Z. Si, H. Gong, and S. C. Zhu, "Learning Active Basis Model for Object Detection and Recognition," International Journal of Computer Vision, pp. 1-38, 2009.
- [19] X. Ren, C. C. Fowlkes, and J. Malik, "Learning probabilistic models for contour completion in natural images," International Journal of Computer Vision, vol. 77, pp. 47-63, 2008.
- [20] A. Y. S. Chia, S. Rahardja, D. Rajan, and M. K. H. Leung, "Structural descriptors for category level object detection," IEEE Transactions on Multimedia, vol. 11, pp. 1407-1421, 2009.
- [21] J. Winn and J. Shotton, "The layout consistent random field for recognizing and segmenting partially occluded objects," in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2006, pp. 37-44.
- [22] V. Ferrari, T. Tuytelaars, and L. Van Gool, "Object detection by contour segment networks," in Lecture Notes in Computer Science vol. 3953, ed, 2006, pp. 14-28.
- [23] K. Mikolajczyk, B. Leibe, and B. Schiele, "Multiple object class detection with a generative model," in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2006, pp. 26-33.
- [24] R. C. Nelson and A. Selinger, "Cubist approach to object recognition," in Proceedings of the IEEE International Conference on Computer Vision, 1998, pp. 614-621.
- [25] H. P. Moravec, "Rover visual obstacle avoidance," in Proceedings of the International Joint Conference on Artificial Intelligence, Vancouver, CANADA, 1981, pp. 785-790.
- [26] M. Varma and A. Zisserman, "A statistical approach to material classification using image patch exemplars," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 31, pp. 2032-2047, 2009.
- [27] P. M. Roth, S. Sternig, H. Grabner, and H. Bischof, "Classifier grids for robust adaptive object detection," in Proceedings of the IEEE Computer Vision and Pattern Recognition, Miami, FL, 2009, pp. 2727-2734.
- [28] Kwong Wing Au, Saad J. Bedros, Keith L. Curtner, "Object classification in video images", US7646922 B2, 2010