A Local Feature-Based Robust Approach for Facial Expression Recognition from Depth Video

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Abstract

Facial expression recognition (FER) plays a very significant role in computer vision, pattern recognition, and image processing applications such as human computer interaction as it provides sufficient information about emotions of people. For video-based facial expression recognition, depth cameras can be better candidates over RGB cameras as a person's face cannot be easily recognized from distance-based depth videos hence depth cameras also resolve some privacy issues that can arise using RGB faces. A good FER system is very much reliant on the extraction of robust features as well as recognition engine. In this work, an efficient novel approach is proposed to recognize some facial expressions from time-sequential depth videos. First of all, efficient Local Binary Pattern (LBP) features are obtained from the time-sequential depth faces that are further classified by Generalized Discriminant Analysis (GDA) to make the features more robust and finally, the LBP-GDA features are fed into Hidden Markov Models (HMMs) to train and recognize different facial expressions successfully. The depth information-based proposed facial expression recognition approach is compared to the conventional approaches such as Principal Component Analysis (PCA), Independent Component Analysis (ICA), and Linear Discriminant Analysis (LDA) where the proposed one outperforms others by obtaining better recognition rates.

Keywords: Depth video, local binary patterns (LBP), generalized discriminant analysis (GDA), hidden Markov models (HMMs)

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1. Introduction

Recently video cameras are very widely used for many surveillance applications such as face or facial expression recognition (FER) [1]-[11]. Hence, FER has attracted a lot attention from the reearch community due to its applications in many areas of image processsing, pattern recognition and computer vision. In this regard, good face analysis can be considered a major concern due to various causes such as the failure of extracting efficient features, feature imappropriate variances among the different epression classes.

1.1 Related Work

For feature extraction from facial expression images, most of the early FER research works utilized Principal Component Analysis (PCA) [2, 3]. PCA is commonly used for dimension reduction. In [2] and [3], the authors also employed PCA to solve FER with the Facial Action Coding System (FACS). In [4], the authors applied PCA to identify Facial Action Units (FAUs) and to recognize the facial expressions. Most of the recent works focused on the emotion specified feature extraction rather than FAU [5-8]. In [5], Linear Discriminant Analysis (LDA) was applied over PCA features of the facial expression images. Recently, Independent Component Analysis (ICA) has been extensively utilized for FER tasks due to its ability to extract local face features [6]. In [6], ICA was used to extract the IC features of facial expression images to recognize the Action Units (AU).

In recent years, local binary patterns (LBP) that was originally proposed for texture analysis to efficiently summarize the local structures of an image have received increasing interest for facial expression representation. The key property of LBP features is their tolerance against illumination changes and their computational simplicity. Hence, LBP has been successfully employed as a local feature extraction method in facial expression recognition [7, 8]. A robust discriminant analysis called General Discriminant Analysis (GDA) has recently been used in different applications where GDA significantly shows the superiority over the traditional feature extraction approaches such as PCA and LDA [11]. Thus, GDA can be a robust tool to be used to obtain better discrimination among the face images from different expressions.

Depth information-based face representation has become very popular nowadays over RGB since the pixel intensities in the depth images are set based on the distance to the camera to provide better expression information than typical RGB images [10]. Moreover, the original identity of a person cannot be obtained easily from the depth videos that would help to resolve privacy issues which cannot be resolved easily when applying RGB videos. Though LBP-based features on RGB images can generate better results than the conventional features on RGB faces but as different people have different face colors, RGB face pixel inteisities would definitley produce problems for LBP to generate a robust person independent expression recognition system. However, LBP-based features on RGB images can produce good recognition results for a person’s face recognition rather than facial expression recognition. So, aforemnetioned discussion indicates it clearly that LBP-based depth face features can produce better results than LBP-based RGB face features as facial expression recognition systems should not be dependent on face colors. Thus, LBP-based features on depth faces should allow one to come up with a robust person independent FER system.

In addition to FER, depth camera image analysis has received a great deal of attention from many researchers in other fields of computer vision and pattern analysis [12-31]. In [12], the authors used depth map sequences to analysis robust features for distinguished human activity analysis. In [14], the authors adopted depth information-based histograms of surface orientation for action recognition. In [17], the authors applied depth motion-based maps to capture motion energies in activity videos to represent different human activities. In [21], the authors considered moving object labeling utilizing RGB as well as Depth videos. In [23], the authors adopted depth based moving object actions with the help of two-layer maximum entropy markov model. In [27], the authors used particle swarm optimization to model two interacting hands from depth images for human pose representatiom. Besides human pose analysis, visual gestural languages such as american sign language is also considered to be a very active field in image processing and computer vision [28-31]. For instance, the sign speak project analyzed transaion of American sign language based on mobile platform [31].

Hidden Markov Model (HMM), a robust tool to model time-sequential events has been very commonly tested for FER [10]. HMM is basically a stochastic model to represent sequential data where the stochastic process is determined by two mechanisms i.e., a Markov chain consisting of a finite number of states and a set of observation probability distributions. At each discrete instant, the process is usually assumed to be in a state and corresponding to that state, an observation is generated.Thus, HMMs can be adopted to model the time-sequential robust features of different facial expressions for a robust FER system.

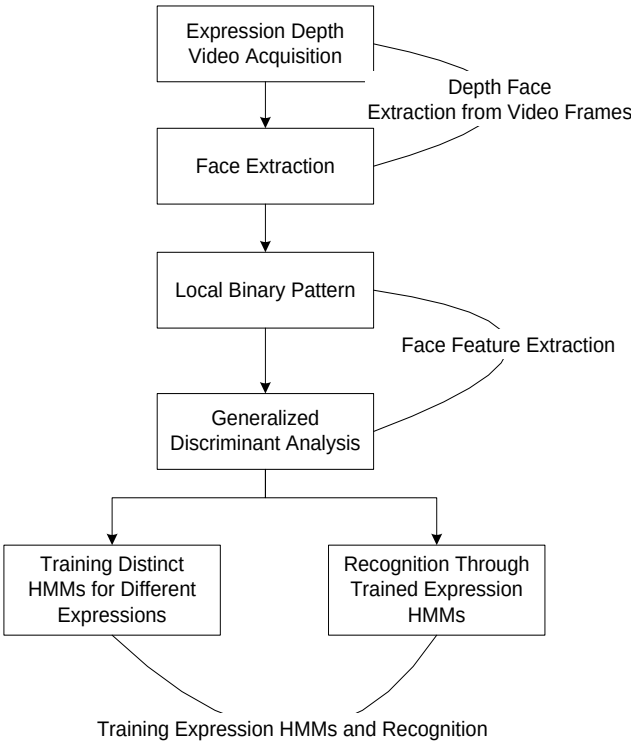


Fig. 1. Architecture of the proposed depth sensor-based FER system.

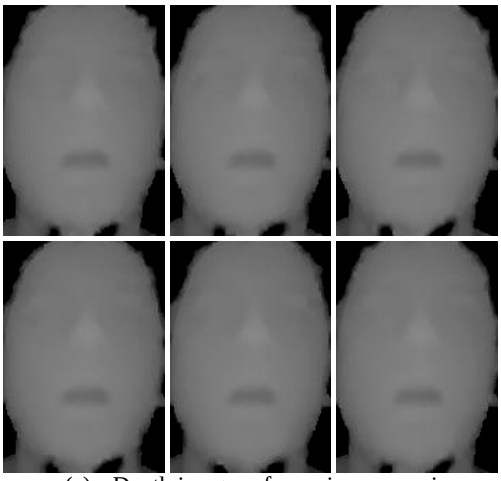
1.2 Proposed Approach

In this work, a novel depth face-based FER approach is proposed utilizing LBP with GDA and HMMs. The local efficient features aee extracted first using LBP and then enahanced by

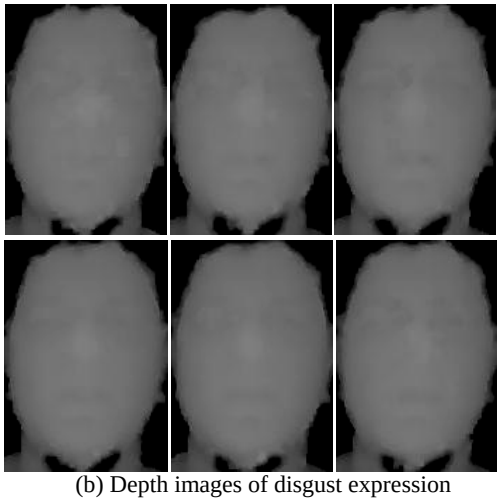
non-linear feature classificattion approach GDA that increases the robustness of the features. The time-sequential feature sequences from each depth video then applied to train each expression HMM to be used later for recognition based on likelihood.

2. Proposed FER Methodology

A strong feature space is first generated via LBP and GDA to be applied with HMMs later for training and testing. **Fig. 1** shows the basic steps of training and testing of expressions through HMMs.



(a) Depth images of surprise expression



(b) Depth images of disgust expression

Fig. 2. Example sequential images of depth facial expression.

2.1 Depth Face Preprocessing

The images of different expressions are captured by a depth camera [10] where the camera generates distance information (i.e., depth) simultaneously for the objects captured by the camera. The depth video represents the range of every pixel in the scene as a gray level intensity (i.e., the longer ranged pixels have darker and shorter ones brighter values or vice

versa). **Fig. 2(a)** and **(b)** show six generalized depth faces from a surprise and disgust expressions respectively.

2.2 LBP Feature Extraction

At a given pixel position (x_c, y_c) with the gray value K_c, local texture T is defined as $T = t(K_c, K_0, K_1, K_2, K_3, K_4, K_5, K_6, K_7)$, where K_i correspond to the gray values of the eight surrounding pixels. To compare the relative intensities between the center pixel and its neighbor pixels, T can be rewritten as

$$T \approx t(s(K_i - K_c)) \quad i = 1, 2, .., 7 \tag{1}$$

where function $s(l)$ is defined as:

$$s(P) = \begin{cases} 0, & P \le 0 \\ 1, & P > 0 \end{cases} \tag{2}$$

Then, the LBP pattern at the given pixel at (x_p, y_p) can be represented as an ordered set of the binary comparisons as:

$$LBP(x_p, y_p) = \sum_{i=0}^{7} s(K_i - K_p) 2^i \tag{3}$$

However, the LBP features from the depth faces can be represented as *D*. **Fig. 3** shows a LBP operator used in this work. The image *L* textual feature is basically represented by the histogram of the LBP map of which the ith bin can be defined as follows

$$H_m = \sum_{x,y} L\{LBP(x, y) = i\} \tag{4}$$

where m is from 1 to n-1 and n the number of the LBP histogram bins where usually $n = 256$. Finally, the whole LBP feature H is expressed as a concatenated sequence of histograms $H = (H^1, H^2, ..., H^r)$, where r is the number of the subregions of the image. Thus, from each depth face image, expression features (i.e., LBP descriptors) are extracted as aforementioned. **Fig. 4** shows a surprise depth expression image is divided into 64 small regions from which LBP histograms are extracted and concatenated into LBP descriptor.

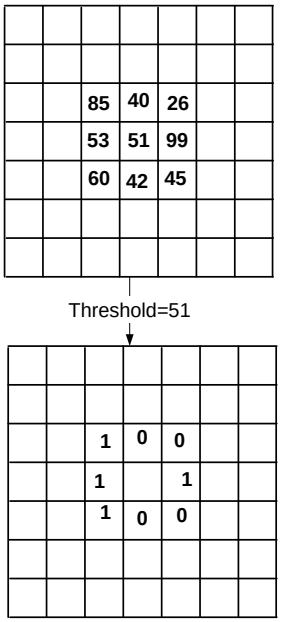


Fig. 3. An LBP operator

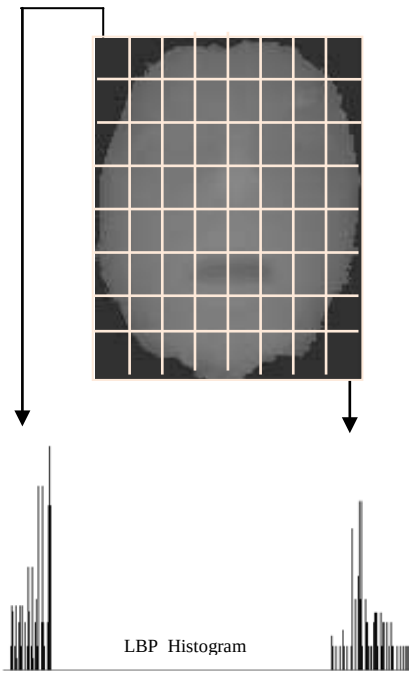


Fig. 4. A surprise expression image is divided into small regions from which LBP histograms are extracted and concatenated into LBP descriptor.

After analyzing the LBP descriptors of all the face depth images, it was noticed that there are some positions from all the positions corresponding to all the face images have values greater than 0. Thus, it is better to consider only those positions of LBP descriptors of a face region and determine the standard dimension of the LBP descriptors for any face. However, the LBP features from the depth faces can be represented as X .

2.3 GDA on LBP

Generalized Discriminant Analysis (GDA) is a discriminant analysis approach that produces an optimal discriminant function, which maps the input into the classification space on which the class identification of the samples is determined. The principal idea of GDA is to map the training depth faces into a high dimensional feature space. The goal of GDA is to maximize following equation as

$$G_{GDA} = \frac{\left| v^T S_B v \right|}{\left| v^T S_T v \right|} \tag{5}$$

where S_B and S_T are the between-class and total scatter matrices respectively in the feature space. Thus, the depth face LBP features X of different expressions can be extended by GDA as

$$D = G_{GDA}^T X. \tag{6}$$

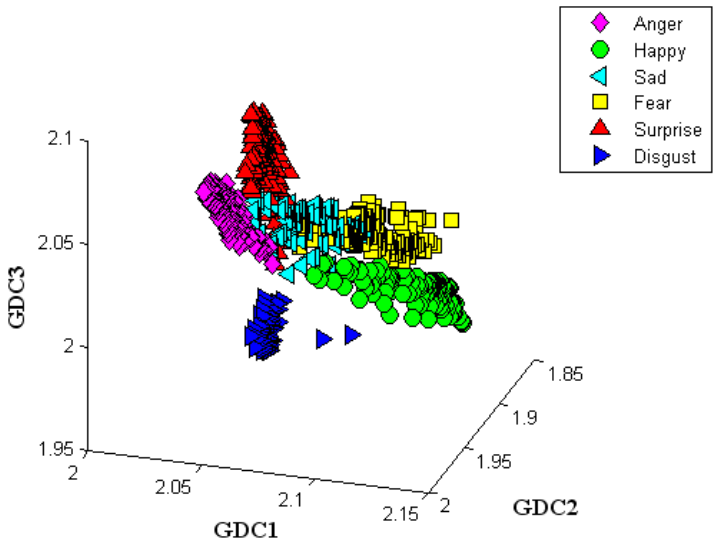


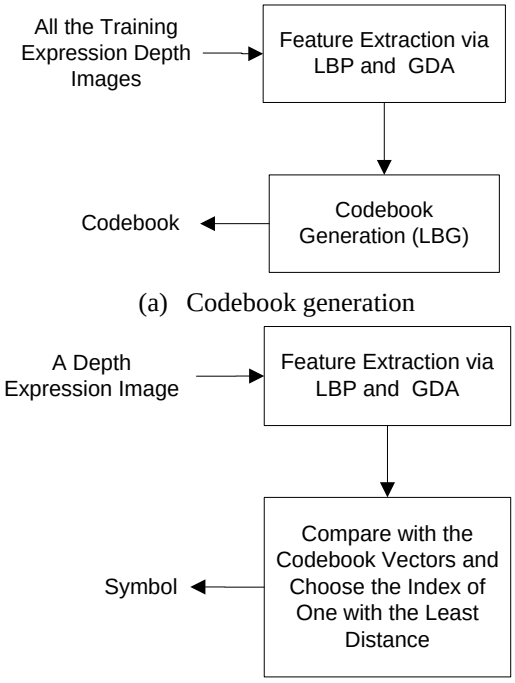
Fig. 5. 3-D plot of LBP-GDA features of depth faces from four expressions.

Fig. 5 shows an exemplar plot of 3-D GDA representation of the LBP features of all the facial expression depth images that shows a good separation among the representation of the depth faces of different classes.

2.4 HMMs for FER

To decode the depth information-based time-sequential facial expression features, discrete HMMs are employed. As discrete HMMs are usually trained and tested with discrete symbol sequences, the features are needed to be symbolized by comparing with the codebook vectors where the codebook is developed by Linde, Buzo and Gray (LBG)'s clustering algorithm on the feature vectors from the training datasets [10]. Once the codebook is obtained, the index

numbers of the codebook vectors are considered as symbols to be used with discrete HMMs. As each facial expression image from the depth expression video clip is converted to a symbol, a clip of T frames will result in T symbols. **Fig. 6** shows the basic steps for codebook generation and symbol selection.



(a) Codebook generation

(b) Symbol selection

Fig. 6. Steps for codebook generation and symbol selection.

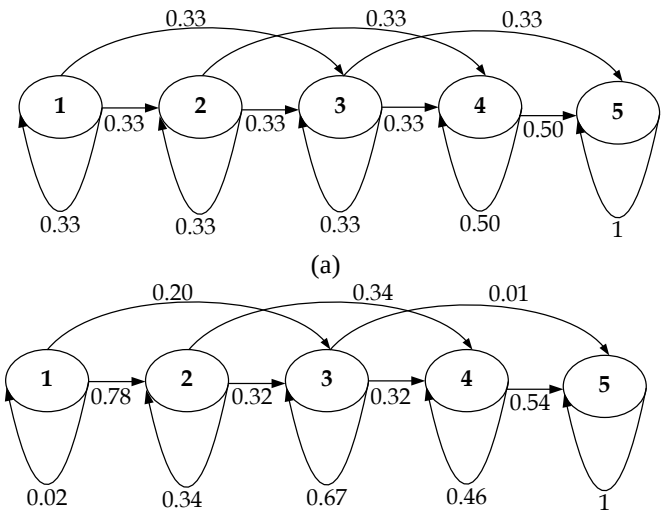


Fig. 7. A HMM transition probabilities for fear expression (a) before and (b) after training.

HMMs have been applied extensively to solve a large number of complex problems in various applications [10]. In this work, each expression is trained using separate HMM *H*. **Fig. 7** depicts the HMM structure used in this work as well as transition probabilities for fear expression before and after training. To test a facial expression video for recognition, the obtained discrete observation symbol sequence S from the corresponding time-sequential depth images is used to determine the proper model by means of highest likelihood Γ computation of all N trained expression HMMs as follows.

$$\Gamma = \arg\max_{k=1}^{N}(P(S \mid H_k)) \tag{6}$$

3. Experimental Results

To conduct the FER experiments, the RGB and depth video databases were built for six different expressions: namely Surprise, Sad, Happy, Disgust, Anger, and Fear. Each expression video clip was of variable length and each expression in each video starts and ends with neutral expression. A total of 20 sequences from each expression were used to build the feature space to project all the expression images later. To train and test each facial expression model, 20 and 40 image sequences were applied respectively. To apply on the HMMs, the features were symbolized using the codebook with the size of 32. To compare the proposed LBP-GDA features with the other conventional feature extraction methods, all methods were implemented with the HMMs to recognize aforementioned six different facial expressions. First of all, RGB camera-based experiments were tried which were followed by the depth videos with the same experimental setups.

Regarding RGB video-based experiments, all the face images were converted to the gray scale first. For the PCA feature case, the eigenvectors were computed from all the dataset and selected 100 eigenvectors to train the HMMs. RGB video-based experimental results are reported in **Table 1**. The average recognition rate obtained using PCA is 58%, the lowest recognition rate in the experiments. Then, LDA on PC features were employed and obtained the improved average recognition rate of 61.50%. Then, ICA highlights the local features of the faces even it is applied on the holistic images. It seems that ICA is a better tool to obtain more relevant features for the expressions. As presented in the table, the average recognition rate utilizing ICA representation of facial expression images is 80.42%, which is higher than the PCA and PCA-LDA recognition rates. Then, LBP was performed on the database and it achieved the recognition rate of 81.25%. To obtain more robust features, GDA was employed as it finds out the best linear as well as nonlinear discrimination among the datasets. Thus, LBP-GDA with HMMs achieved the total average recognition rate of 84.17%. Thus, LBP-GDA showed its superiority over the other feature extraction methods by achieving the highest recognition rate.

For depth camera-based experiments, the experiential setups were followed as RGB camera-based work. The depth video-based FER results are shown in **Table 2**. The average recognition rate using PCA on depth faces is 62%. Applying LDA on PC features, the improved average recognition rate is 65%. The mean recognition rate utilizing ICA representation on the depth facial expression images is 83.50%, which is higher than that of depth face-based FER applying PCA as well as PCA-LDA features. Then, LBP was tried on the same database that achieved the average recognition rate of 89.17%. Finally, LBP-GDA was employed and achieved the superior average recognition rate of 95.83%. Thus, LBP-GDA features with HMM for depth face-based FER showed its superiority over the other feature

extraction methods including RGB camera-based all approaches in the sense of achieving the highest recognition rate.

Fig. 8 depicts the mean recogniton performances of different approaches using RGB and depth videos to the FER systems where LBP-GDA features on depth faces shows its superiority over all others.

Table 1. FER experimental results using RGB face-based different approaches (%)

Approach	Expression	Recognition Rate	Mean
PCA	Anger	40	58
	Happy	45	
	Sad	70	
	Surprise	75	
	Fear	60	
	Disgust	65	
LDA	Anger	50	61.50
	Happy	55	
	Sad	72.50	
	Surprise	75	
	Fear	55	
	Disgust	70	
ICA	Anger	77.50	80.42
	Happy	80	
	Sad	82.50	
	Surprise	80	
	Fear	82.50	
	Disgust	80	
LBP	Anger	80	81.25
	Happy	80	
	Sad	82.50	
	Surprise	82.50	
	Fear	82.50	
	Disgust	80	
LBP-GDA	Anger	85	84.17
	Happy	85	
	Sad	82.50	
	Surprise	82.50	
	Fear	85	
	Disgust	85	

Table 2. FER experimental results using depth face-based different approaches (%)

Approach	Expression	Recognition Rate	Mean
PCA	Anger	50	62
	Happy	50	
	Sad	70	
	Surprise	80	
	Fear	60	
	Disgust	65	
LDA	Anger	55	65
	Happy	60	
	Sad	75	
	Surprise	75	
	Fear	60	
	Disgust	70	
ICA	Anger	80	83.50
	Happy	82.50	
	Sad	85	
	Surprise	85	
	Fear	85	
	Disgust	82.50	
LBP	Anger	87.50	89.17
	Happy	90	
	Sad	90	
	Surprise	92.50	
	Fear	85	
	Disgust	90	
LBP-GDA	Anger	97.50	95.83
	Happy	95	
	Sad	95	
	Surprise	97.50	
	Fear	95	
	Disgust	95	

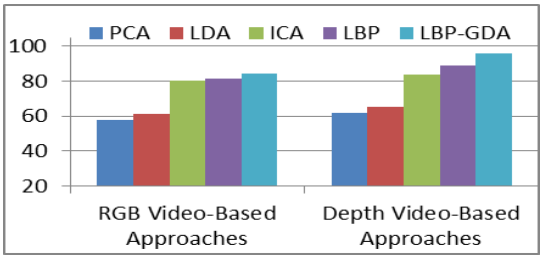


Fig. 8. Mean recognition rates of different approaches based on RGB and depth input videos to FER systems.

4. Conclusion

FER has attracted a lot of researchers in many important research areas such as computer vision and image processing over the last decade. Human computer interaction through facial expressions plays a very significant role in many applications such as telemedicine, smart home healthcare, and social interactions. In such kind of applications, RGB camera may not be a good choice to be used due to some privacy concerns which shows the appropriateness of the use of depth cameras in person independent FER where a person's identity can be hidden. A typical video-based FER system consists of three modules such as preprocessing, feature extraction, and finally recognition. The facial expression features are very sensitive to noise as well as illumination and hence one expression features can become merged with the features of other expression that can lead weak FER system as separation of features of different expressions can be quite tough. Therefore, we have focused on very strong feature space generation that can contribute significantly in separation the features of different expressions that has definitely leaded us to achieve a robust FER system. Thus, in this work, a depth video-based robust FER system has been proposed using LBP-GDA features for facial expression feature extraction and HMM for recognition. The proposed method has been compared with other traditional approaches and the proposed FER approach achieved remarkably improved performance over others. However, the proposed system can still be analyzed further for deploying it to real time environments with different complex parameters.

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