MULTIVIEW FACE RECOGNITION USING ENHANCED GABOR FILTER WITH LOCAL DIRECTIONAL NUMBER PATTERN (LDN)

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ABSTRACT

In this paper, we propose a face descriptor, Local Directional Number Pattern (LDN), for robust face recognition that encodes the structural information and the intensity variations of the face’s texture. LDN encodes the structure of a local neighborhood by analyzing its directional information. Consequently, we compute the edge responses in the neighborhood, in eight different directions with a compass mask. The 2-FFC of Gabor, PCA and ICA filters thus yields three offspring sets: (1) Gabor filters solely, (2) Gabor-PCA filters, and (3) Gabor-ICA filters, to render the learning-free and the learning-based 2-FFC descriptors. To facilitate a sensible Gabor filter selection for ग-FFC, the 40 multiscale, multi-orientation Gabor filters are condensed into 8 elementary filters. Aside from that, an average histogram pooling operator is employed to leverage the □-FFC histogram features, prior to the final whitening PCA compression. The empirical results substantiate that the 2-FFC descriptors prevail over, or on par with, other face descriptors on both identification and verification tasks. We found that the inclusion of multiple encoding levels produces an improvement in the detection process. Moreover, we test our descriptor with different masks to analyze its performance in different face analysis tasks.

Index Terms—Gabor filters, PCA filters, ICA filters, filter convolution, face recognition

I INTRODUCTION

1.1 INTRODUCTION TO IMAGE PROCESSING

Face recognition, including identification and verification tasks, is highly challenging in practice due to wide intra class variability in pose and expression, and other disturbances, including illumination, occlusion, misalignment, corruption, just to name a few. An ideal face descriptor, regardless of handcrafted or learning-based, should be invariant to these intra-class difficulties. A plausible remedy is the longstanding filter bank (FB) approaches, where the local structure of overlapping neighborhoods is featured by means of linear local convolutions, or local matches.

In imaging science, image processing is any form of signal processing for which the input is an image, such as a photograph or video frame; the output of image processing may be either an image or a set of characteristics or parameters related to the image. Most image processing techniques involve treating the image as a two-dimensional signal and applying standard signal-processing techniques to it.

Image processing usually refers to digital image processing, but optical and analog image processing also are possible. This article is about general techniques that apply to all of them. The acquisition of images (producing the input image in the first place) is referred to as imaging.

Closely related to image processing are computer graphics and computer vision. In computer graphics, images are manually made from physical models of objects, environments, and lighting, instead of being acquired (via imaging devices such as cameras) from natural scenes, as in most animated movies. Computer vision, on the other hand, is often considered high-level image processing out of which a machine/computer/software intends to decipher the physical contents of an image or a sequence of images (e.g., videos or 3D full-body magnetic resonance scans).

In modern sciences and technologies, images also gain much broader scopes due to the ever growing importance of scientific visualization (of often large-scale complex scientific/experimental data). Examples include microarray data in genetic research, or real time multi-asset portfolio trading in finance.

1.2 FACE IMAGE ANALYSIS

Face recognition has a critical role in biometric system attractive for numerous applications including visual surveillance and security. Because of the general public acceptance of face images on various documents, face recognition has a great potential to become the next generation biometric technology of choice. Face images are also the only biometric information available in some legacy databases and international terrorist watch-lists and can be acquired even without subjects' cooperation.

Though there has been a great deal of progress in face detection and recognition in the last few years, many problems remain unsolved. Research on face detection must confront with many challenging problems, especially when dealing with outdoor illumination, pose variation with large rotation angles, low image quality, low resolution, occlusion, and background changes in complex real-life scenes. The design of face recognition algorithms that are effective over a wide range of viewpoints, complex outdoor lighting, occlusions, facial expressions, and aging of subjects, is still a major area of research. Before one claims that the facial image processing / analysis system is reliable, rigorous testing and verification on real-world datasets must be performed, including databases for face analysis and tracking in digital video. 3D head model assisted recognition is another research area where new solutions are urgently needed to enhance robustness of today's recognition systems and enable real-time, face-oriented processing and analysis of visual data. Thus, vigorous research is needed to solve such outstanding challenging problems and propose advanced solutions and systems for emerging applications of facial image processing and analysis.

1.3 FACE DETECTION

Face detection is a computer technology that determines the locations and sizes of human faces in digital images. It detects face and ignores anything else, such as buildings, trees and bodies.

Face detection can be regarded as a more general case of face localization. In face localization, the task is to find the locations and sizes of a known number of faces (usually one). In face detection, face is processed and matched facial expression, e.g. smile, lip movement, will not match the face.

Face detection is also the psychological process by which we locate and attend to faces in a visual scene. Research shows that our ability to detect faces is affected by a range of visual properties such as color and orientation.

Face detection can be regarded as a specific case of object-class detection. In object class detection, the task is to find the locations and sizes of all objects in an image that belong to a given class. Examples include upper torsos, pedestrians, and cars.

Face-detection algorithms focus on the detection of frontal human faces. It is analogous to image detection in which the image of a person is matched bit by bit. Image matches with the image stores in database. Any facial feature changes in the database will invalidate the matching process.

1.4 APPLICATION

Facial recognition

Face detection is used in biometrics, often as a part of (or together with) a facial recognition system. It is also used in video surveillance, human computer interface and image database management.

Photography

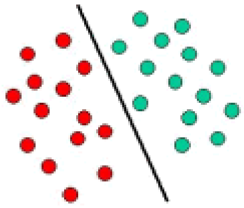
Some recent digital cameras use face detection for autofocus.[4] Face detection is also useful for selecting regions of interest in photo slideshows that use a pan-and-scale Ken Burns effect.

Marketing

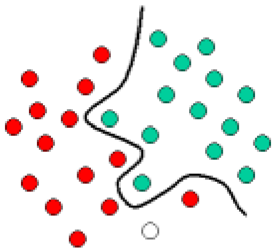
Face detection is gaining the interest of marketers. A webcam can be integrated into a television and detect any face that walks by. The system then calculates the race, gender, and age range of the face. Once the information is collected, a series of advertisements can be played that is specific toward the detected race/gender/age. An example of such a system is called Optima Eyes and is integrated into the Am screen digital signage system.

Support Vector Machines (SVM) Introductory Overview

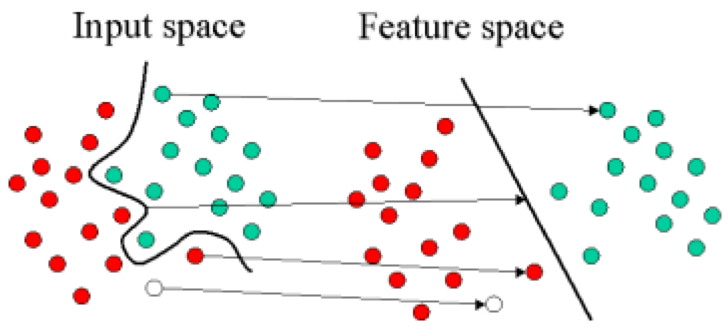
Support Vector Machines are based on the concept of decision planes that define decision boundaries. A decision plane is one that separates between a set of objects having different class memberships. A schematic example is shown in the illustration below. In this example, the objects belong either to class GREEN or RED. The separating line defines a boundary on the right side of which all objects are GREEN and to the left of which all objects are RED. Any new object (white circle) falling to the right is labeled, i.e., classified, as GREEN (or classified as RED should it fall to the left of the separating line).



The above is a classic example of a linear classifier, i.e., a classifier that separates a set of objects into their respective groups (GREEN and RED in this case) with a line. Most classification tasks, however, are not that simple, and often more complex structures are needed in order to make an optimal separation, i.e., correctly classify new objects (test cases) on the basis of the examples that are available (train cases). This situation is depicted in the illustration below. Compared to the previous schematic, it is clear that a full separation of the GREEN and RED objects would require a curve (which is more complex than a line). Classification tasks based on drawing separating lines to distinguish between objects of different class memberships are known as hyper plane classifiers. Support Vector Machines are particularly suited to handle such tasks.



The illustration below shows the basic idea behind Support Vector Machines. Here we see the original objects (left side of the schematic) mapped, i.e., rearranged, using a set of mathematical functions, known as kernels. The process of rearranging the objects is known as mapping (transformation). Note that in this new setting, the mapped objects (right side of the schematic) is linearly separable and, thus, instead of constructing the complex curve (left schematic), all we have to do is to find an optimal line that can separate the GREEN and the RED objects.



Support Vector Machine (SVM) is primarily a classier method that performs classification tasks by constructing hyper planes in a multidimensional space that separates cases of different class labels. SVM supports both regression and classification tasks and can handle multiple continuous and categorical variables. For categorical variables a dummy variable is created with case values as either 0 or 1. Thus, a categorical dependent variable consisting of three levels, say (A, B, C), is represented by a set of three dummy variables:

A: {1 0 0}, B: {0 1 0}, C: {0 0 1}

To construct an optimal hyper plane, SVM employs an iterative training algorithm, which is used to minimize an error function.

II LITERATURE SURVAY

T. Jabid, M. H. Kabir, and O. Chae, Robust facial expression recognition based on local directional pattern

Automatic facial expression recognition has many potential applications in different areas of human computer interaction. However, they are not yet fully realized due to the lack of an effective facial feature descriptor. In this paper, we present a new appearance-based feature descriptor, the local directional pattern (LDP), to represent facial geometry and analyze its performance in expression recognition. An LDP feature is obtained by computing the edge response values in 8 directions at each pixel and encoding them into an 8 bit binary number using the relative strength of these edge responses. The LDP descriptor, a distribution of LDP codes within an image or image patch, is used to describe each expression image. The effectiveness of dimensionality reduction techniques, such as principal component analysis and AdaBoost, is also analyzed in terms of computational cost saving and classification accuracy.

Two well-known machine learning methods, template matching and support vector machine, are used for classification using the Cohn-Kanade and Japanese female facial expression databases. Better classification accuracy shows the superiority of LDP descriptor against other appearance-based feature descriptors. Facial expression provides the most natural and immediate indication about a person’s emotions and intentions. Therefore, automatic facial expression analysis is an important and challenging task that has had great impact in such areas as human-computer interaction and data-driven animation. Furthermore, video cameras have recently become an integral part of many consumer devices and can be used for capturing facial images for recognition of people and their emotions.

This ability to recognize emotions can enable customized applications. Even though much work has already been done on automatic facial expression recognition higher accuracy with reasonable speed still remains a great challenge [8]. Consequently, a fast but robust facial expression recognition system is very much needed to support these applications. The most critical aspect for any successful facial expression recognition system is to find an efficient facial feature representation [9]. An extracted facial feature can be considered an efficient representation if it can fulfill three criteria: first, it minimizes within-class variations of expressions while maximizes between-class variations; second, it can be easily extracted from the raw face image; and third, it can be described in a low dimensional feature space to ensure computational speed during the classification step.

The goal of the facial feature extraction is thus to find an efficient and effective representation of the facial images which would provide robustness during recognition process. Two types of approaches have been proposed to extract facial features for expression recognition: a geometric feature-based system and an appearance-based system. In the geometric feature extraction system, the shape and Robust Facial Expression Recognition Based on Local Directional Pattern location of facial components are considered, and geometric relationships between these components are used to form a feature vector. These geometric relationships may be example positions, distances, and angles.

For instance, Zhang and others used the geometric positions of 34 fiducial points as facial features to represent facial images. Another widely-used facial description is the Facial Action Coding System, where facial expressions are represented by one or more action units (AUs). Valstar and others presented detection by classifying features calculated from tracked fiducial facial points and urged that geometric approaches have similar or better performance than appearance-based approaches in facial expression analysis.

However, geometric representation of facial geometry requires accurate and reliable facial component detection and tracking, which are difficult to accommodate in many situations. The appearance-based system models the face images by applying an image filter or filter banks on the whole face or some specific regions of the face to extract changes in facial appearance. Principal component analysis (PCA) has been widely applied to extract features for face recognition. PCA is primarily used in a holistic manner. More recently, independent component analysis (ICA) enhanced ICA and Gabor wavelet have been utilized to extract facial feature either from whole-face or specific face regions for modeling facial changes.

Donato and others performed a comprehensive analysis of different techniques, including PCA, ICA, local feature analysis, and Gabor wavelet, to represent images of faces for facial action recognition and demonstrate that the best performance can be achieved by ICA and Gabor wavelet. However, convoluting a facial image with multiple Gabor filters of multiple scales and orientations makes the Gabor representation very intensive as regards time and memory. Among the appearance-based feature extraction methods, the local binary pattern (LBP) method which was originally introduced for the purpose of texture analysis and its variants were used as a feature descriptor for facial expression representation.

The LBP method is computationally efficient and robust to monotonic illumination changes. However, it is sensitive to non-monotonic illumination variation and also shows poor performance in the presence of random noise. The local directional pattern (LDP) method, a more robust facial feature proposed by Jabid and others demonstrated better performance for face recognition compared to LBP. In this work, we have analyzed the performance of the proposed LDP feature in characterizing different facial expression. We empirically study the effectiveness of facial image representation based on LDP for recognizing human expression. The performance of this representation is evaluated using template matching and support vector machine (SVM). Extensive experiments with two widely-used expression databases, namely, the Cohn-Kanade (CK) facial expression database and the Japanese female facial expression (JAFFE) database, demonstrate that the LDP feature is more robust in extracting the facial features, and it is also superior in classifying expressions compared to LBP and Gabor wavelet features. We also find that the LDP method performs stably and robustly over a useful range of lower resolution face images.

ADVANTAGES

- Well suitable for real time application
- Maintain a high recognition rate

DISADVANTAGES

- It is relatively more expensive than that of LBP
- It needs to compute different edge responses with a compass mask

III THEORETICAL BACKGROUND

3.1 PROBLEM IDENTIFICATION

A novel algorithm to extract moving objects from video sequences is proposed in this paper. The proposed algorithm employs a flashing system to obtain an alternate series of lit and unlit frames from a single camera. For each unlit frame, the proposed algorithm synthesizes the corresponding lit frame using a motion-compensated interpolation scheme. Then, by comparing the unlit frame with the lit frame, we construct the sensitivity map, which provides depth cues. In addition to the sensitivity term, color, coherence, and smoothness terms are employed to define an energy function, which is minimized to yield segmentation results. Moreover, they developed a faster version of the proposed algorithm, which reduces the computational complexity significantly at the cost of slight performance degradation. Experiments on various test sequences show that the proposed algorithm provides high-quality segmentation results.

DISADVANTAGES

- However, they may not provide accurate results for sequences with no or small object motions.
- The disparity estimation is another challenging task, requiring heavy computational loads.
- The interactions prevent them from being used in applications in which full automation is required

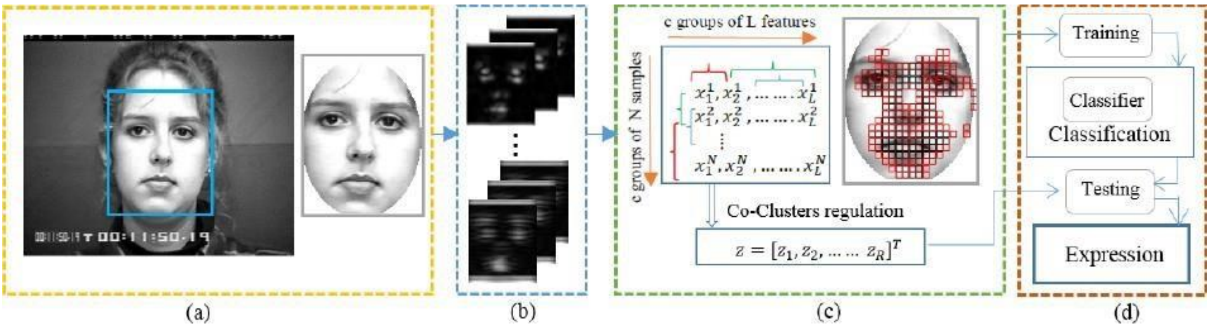
3.2 PROBLEM SOLVING

In photography, low depth of field (DOF) is an important technique to emphasize the object of interest (OOI) within an image. Thus, low DOF images are widely used in the application area of macro, portrait or sports photography. When viewing a low DOF image, the viewer implicitly concentrates on the regions that are sharper regions of the image and thus segments the image into regions of interest and non regions of interest which has a major impact on the perception of the image. Thus, a robust algorithm for the fully automatic detection of the OOI in low DOF images provides valuable information for subsequent image processing and image retrieval. In this paper we propose a robust and parameter less algorithm for the fully automatic segmentation of low DOF images. We compare our method with three similar methods and show the superior robustness even though our algorithm does not require any parameters to be set by hand. The experiments are conducted on a real world data set with high and low DOF images.

ADVANTAGES

- Improve the classification accuracy because the extraction of features can be restricted to the subset of pixels contained in the OOI of the images.
- Automatic segmentation of OOIs in low DOF images to improve search quality

In this section, we describe the general framework of our facial expression recognition (FER) system based on co-clustering.



The system consists of three modules: Pre-processing, Facial feature extraction, and Recognition.

- Images are first pre-processed to normalize the face geometry, and then features are extracted using a bank of Gabor filters.

IV SYSTEM IMPLEMETATION

4.1. INPUT IMAGE

To align the facial features, image normalization is necessary. We first detect the face using Viola's face detector and then normalize the images based on the eye positions to deal with the head rotation and imperfect localization. Cropping is done at a later stage using the ellipse face mask. Furthermore, despite the presence of illumination variations in images, no intensity normalization was performed because the Gabor wavelets are gray-scale invariant. We tested our method for face recognition in several data- bases: FERET, Yale B, Extended Yale B, LFW, and CAS-PEAL. FERET: We tested the performance of the methods, for the face recognition problem, in accordance to the CSU Face Identification Evaluation System with images from the FERET database. In this problem, given a gallery containing labeled face images of several individuals (one or more face images for each person), we classify a new set of probe images.

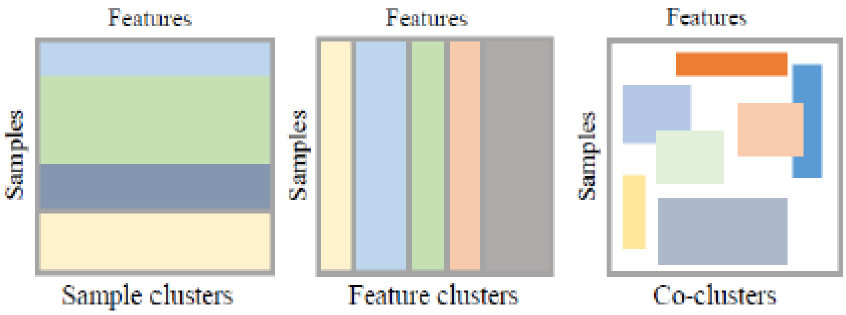
4.2. GABOR WAVELETS FOR IMAGE REPRESENTATION

Wavelet filters are capable of decomposing an image into appropriate texture features.
Due to their relevance to the human visual system, multi-channel filtering has gained much attention in computer vision for recognition tasks.

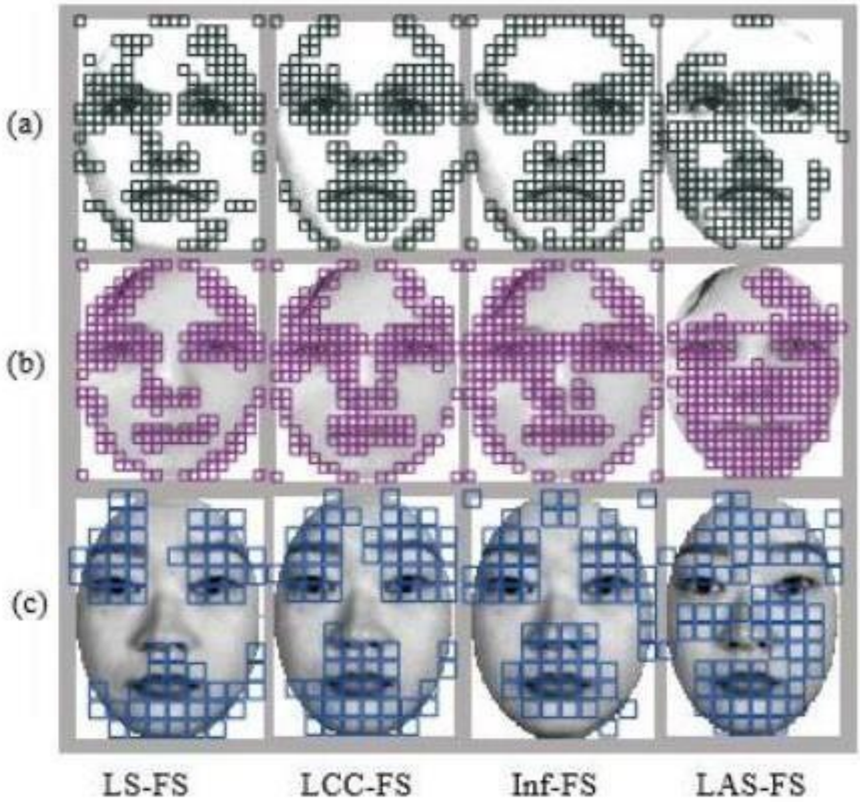
4.3. GABOR FUNCTION

Feature extraction using a bank of Gabor filters

4.4. CO-CLUSTERING BASED FEATURE SELECTION (CCFS) METHOD



Co-clustering is an unsupervised learning procedure that targets the association of rows and columns in the feature matrix, yielding distinct “checkerboard” patterns in the data matrix. Recently, co-clustering methods have gained much popularity and found many applications in data mining and biological studies. Classical clustering techniques perform classification in one direction only to deal with the similarities of samples (in rows) as reflected by their features (in all columns) of a matrix. They typically assume that samples in a particular cluster share exactly the same properties overall available features.



Therefore, conventional clustering methods reflect the global patterns of samples and ignore the local patterns among samples and features. In reality, different samples in a data matrix may have properties reflected by different features. The co-clustering approaches identify the local patterns in the data matrix that are apparently not visible.

4.5 SVD CONNECTION

To detect co-clusters from a data matrix, a number of co-clustering approaches have been developed based on matrix factorization techniques, including singular vector decomposition (SVD) and its higher order forms. This paper focuses on SVD to decompose the facial expression data matrix.

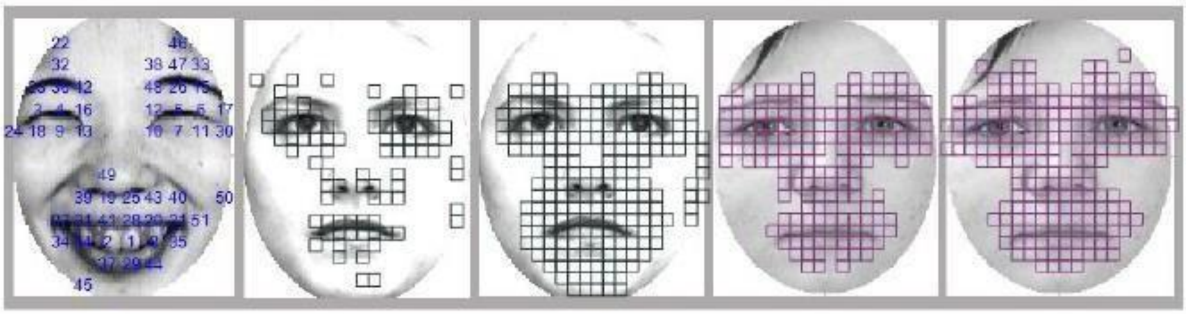
SVD has been explored to detect arbitrary combinations of the key features as co-clusters. In order to extract useful coherent patterns from the data and overcome the noise influence, only the first several singular vectors corresponding to the largest singular values are selected. In this way, SVD can produce more localized feature representations of both expression samples and features.

4.6 CO-CLUSTERING

In the facial expression feature matrix, a set of similar facial expression samples are expected to have a correlation in terms of a set of features, as shown in Fig. 1.Weexplore these sub matrices in the dominant singular vectors space.

4.7 FEATURE SELECTION

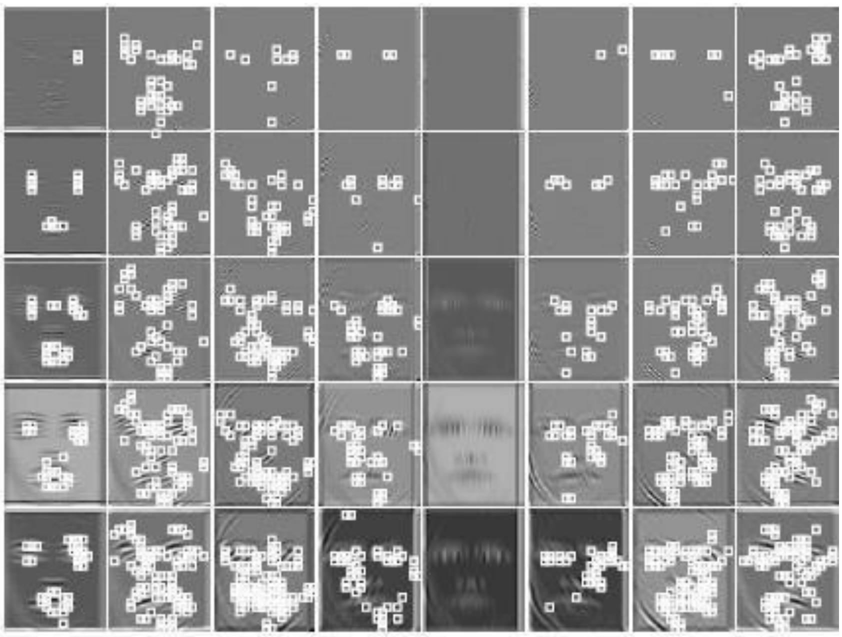
In terms of local patterns, the co-clustering method exhibits an overwhelming advantage over hard clustering. In co-clustering, we are able to identify a small subset of sample and feature correspondences, where several co-clusters can partially overlap.



(a) (b) (c) (d) (e)

4.8 CLASSIFICATION USING MULTICLASS SVMS

For facial expression recognition, the final task of classification is performed with SVM, which is a binary discriminant classifier built based on the structural risk minimization principle that creates maximum margin hyper-plane among two classes. In our experiments, we used the multiclass SVMs and the one against all strategy. Detailed illustration about multiclass SVMs and their formulation can be found in. Here we briefly present the optimization problem of multiclass SVMs



V CONCLUSION & FUTURE WORK

5.1 CONCLUSION

In this paper we introduced a novel encoding scheme, LDN, that takes advantage of the structure of the face's textures and that encodes it efficiently into a compact code. LDN uses directional information that is more stable against noise than intensity, to code the different patterns from the face's textures. Additionally, we analyzed the use of two different compass masks (a derivative-Gaussian and Kirsch) to extract this directional information, and their performance on different applications. Gabor wavelets are useful for facial expression recognition, but the number of features is very high as compared to the number of available samples. Among this over-whelming number of features, only a small fraction may be needed. Feature selection in this regard improves the scalability (defying the curse of dimensionality) and reduces the identity bias when specific regions are located. In this paper, a novel method for feature election in facial expression recognition based on co-clustering is pro-posed. Our method is able to reveal the saliency of face regions by selecting a small number of dominant features from Gabor wavelets features. Experiments have been conducted on widely used benchmark facial expression image databases. With the JAFFE and MMI databases, we achieved recognition rates of 95.31% and 94.09% respectively using SVM on reduced feature sets. With the CK+ database, we obtained the ac-curacy of 96.05% by using only 20% of the features. An interesting aspect of this work is that when a feature set containing as little as 0.9% of the entire feature data were used, we could still obtain an accuracy of 90.23%.

5.2 FUTURE ENHANCEMENT

Furthermore, we found that the combination of different sizes (small, medium and large) gives better recognition rates for certain conditions Also, we evaluated LDN under expression, time lapse and illumination variations, and found that it is reliable and robust throughout all these conditions, unlike other methods. For example, Gradient faces had excellent results under illumination variation but failed with expression and time lapse variation. Also, LBP and LDiP recognition rate deteriorates faster than LDN in presence of noise and illumination changes.

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