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MULTIVIEW FACE RECOGNITION USING ENHANCED GABOR FILTER WITH ATTRIBUTE FEATURE EXTRACTION (AFE)

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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 □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.

I INTRODUCTION

1.1 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 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

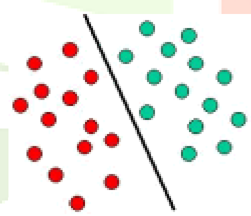
Some recent digital cameras use face detection for autofocus.[4] Face detection is also useful for selecting regions of interest in photo slideshows that use a pan-and-scale Ken Burns effect.

Marketing

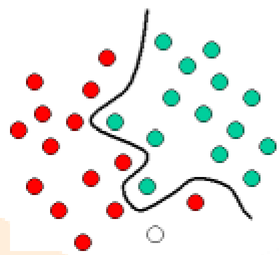
Face detection is gaining the interest of marketers. A webcam can be integrated into a television and detect any face that walks by. The system then calculates the race, gender, and age range of the face. Once the information is collected, a series of advertisements can be played that is specific toward 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).

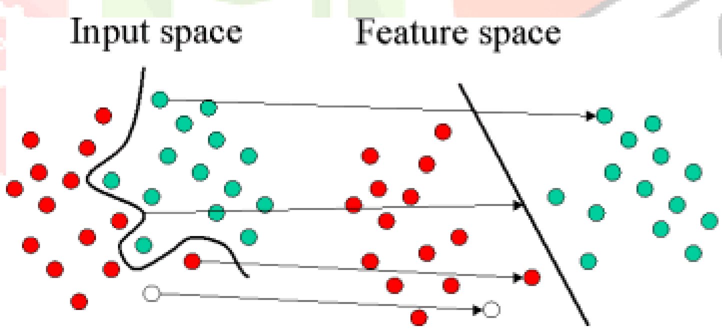


The above is a classic example of a linear classifier, i.e., a classifier that separates a set of objects into their respective groups (GREEN and RED in this case) with a line. Most classification tasks, however, are not that simple, and often more complex structures are needed in order to make an optimal 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

N. Bourbakis; A. Esposito; and D. Kavraki Extracting and associating Meta features for understanding people's emotional behaviour: Face and speech:

In face analysis, a key issue is the descriptor of the face appearance. The efficiency of the descriptor depends on its representation and the ease of extracting it from the face. Ideally, a good descriptor should have a high variance among classes (between different persons or expressions), but little or no variation within classes (same person or expression in different conditions). These descriptors are used in several areas, such as, facial expression and face recognition. There are two common approaches to extract facial features: geometric-feature-based and appearance-based methods. The former, encodes the shape and locations of different facial components, which are combined into a feature vector that represents the face. An instance of these methods is the graph-based methods, which use several facial components to create a representation of the face and process it. Moreover, the Local-Global Graph algorithm is an interesting approach that uses Voronoi tessellation and Delaunay graphs to segment local features and builds a graph for face and expression recognition. These features are mixed into a local graph, and then the algorithm creates a skeleton (global graph) by interrelating the local graphs to represent the topology of the face. Furthermore, facial features are widely used in expression recognition, as the pioneer work of Ekman and Friesen identifying six basic emotions produced a system to categorize the expressions, known as Facial Action Coding System, and later it was simplified to the Emotional Facial Action Coding System. However, the geometric-feature-based methods usually require accurate and reliable facial feature detection and tracking, which is difficult to accommodate in many situations. The appearance-based methods use image filters, either on the whole-face, to create holistic features, or some specific face-region, to create local features, to extract the appearance changes in the face image. The performance of the appearance-based methods is excellent in constrained environment but their performance degrades in environmental variation. Emotion is a research area that has received much attention during the last 10 years, both in the context of speech synthesis, image understanding as well as in automatic speech recognition, interactive dialogues systems and wearable computing. There are promising studies on the emotional behavior of people, mainly based on human observations. Only a few are based on automatic machine detection due to the lack of Information Technology and Engineering (ITE) techniques that can make available a deeper and large-scale noninvasive analysis and evaluation of people's emotional behaviour and provide tools and support for helping them to overcome social barriers. The present paper reports a study for extracting and associating emotional meta-features to support the development of emotionally rich man–machine interfaces (interactive dialogue systems and intelligent avatars).

ADVANTAGES

- The strong need for user- friendly systems that can secure our assets and protect our privacy without losing our identity in a sea of numbers is obvious.
- The experiment results show that the algorithm reduces the dimension of face feature and finds a best subspace for the classification of human face.

DISADVANTAGES

- Need to improve the classification result
- The recognition is somewhat degraded if the noise presents in images

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

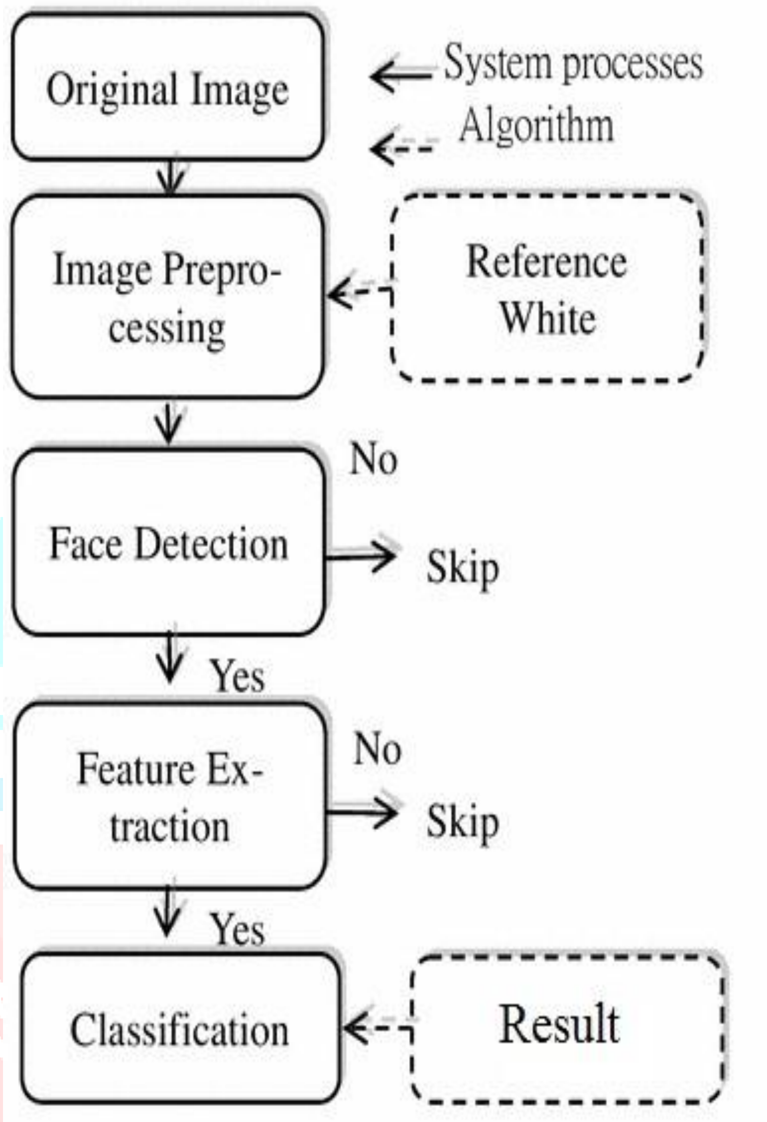
3.2 PROBLEM SOLVING

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

3.3 SYSTEM ARCHITECTURE



IV SYSTEM IMPLEMETATION

4.1. INPUT IMAGE

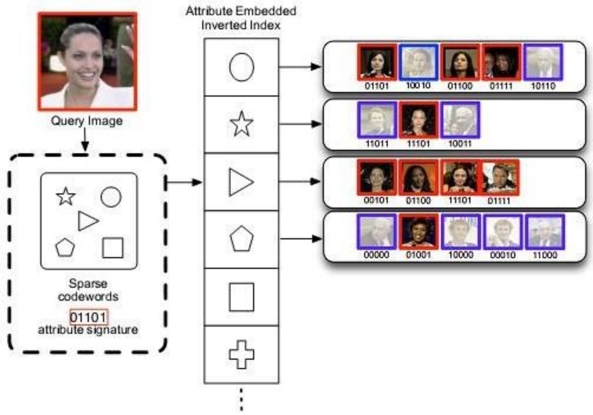
We tested our method for face recognition in several data- bases: FERET, Yale B, Extended Yale B, LFW, and CAS-PEAL. Moreover, we cropped and normalized all images to 100×100 pixels, based on the ground truth positions of the two eyes and mouth when available, or used a face detector to crop the face. In our experiments, every image is partitioned into 10 ×10 regions for all the methods. 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 ness set of probe images. Thus, we used fa image set as gallery and the other four sets as probe images. These sets are fb, for expression variation, fc, for illumination variation, dupI and dupII, for time lapse variation. (Note that in the FERET methodology these datasets are for age variation testing. However the time between images is not significant for age variation. Instead, we associate this factor with time lapse variation).

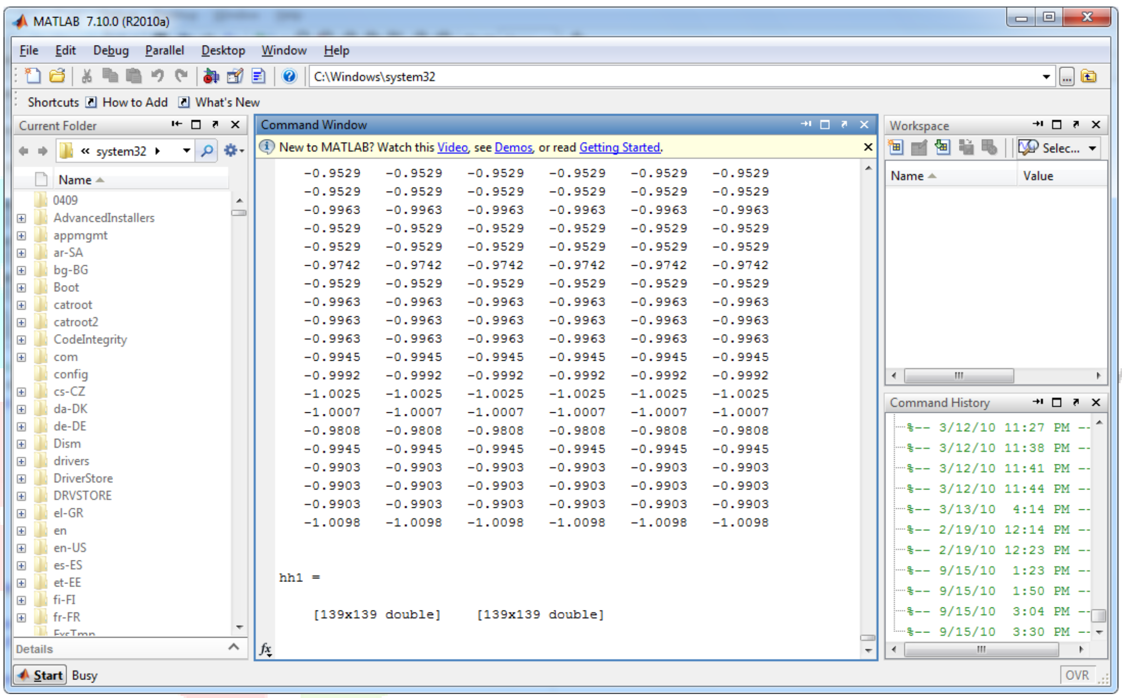
4.2. APPLY LOCAL DIRECTIONAL NUMBER PATTERN DESCRIPTOR

The proposed Local Directional Number Pattern (LDN) is a six bit binary code assigned to each pixel of an input image that represents the structure of the texture and its intensity transitions. As previous research showed, edge magnitudes are largely insensitive to lighting changes. Consequently, we create our pattern by computing the edge response of the neighborhood using a compass mask, and by taking the top directional numbers, that is, the most positive and negative directions of those edge responses. We illustrate this coding scheme in Fig. 1. The positive and negative responses provide valuable information of the structure of the neighborhood, as they reveal the gradient direction of bright and dark areas in the neighborhood. Thereby, this distinction, between dark and bright responses, allows LDN to differentiate between blocks with the positive and the negative direction swapped (which is equivalent to swap the bright and the dark areas of the neighborhood, as shown in the middle of Fig. 1) by generating a different code for each instance, while other methods may mistake the swapped regions as one. Furthermore, these transitions occur often in the face, for example, the top and bottom edges of the eyebrows and mouth have different intensity transitions. Thus, it is important to differentiate among them; LDN can accomplish this task as it assigns a specific code to each of them.

4.3. ATTRIBUTE BASED SEARCH

Query image find out the image attribute like vice (pixel of face, hair, eyes, nose, mouth, each and every part verify it). So this method help to used Content-based image retrieval (CBIR) query by image content (QBIC), Edge detection technique (EDT).its helps to use identify the image attribute. And also data base image search using this technique in identifying the image attribute. We divide the sparse representation into multiple segments based on the number of attributes, and each segment of sparse representation is generated depending on single attribute.

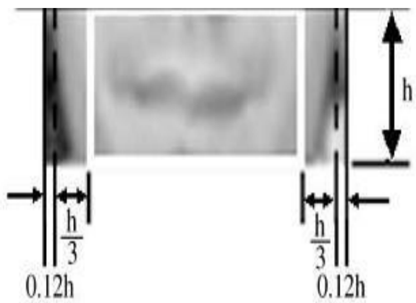




4.4. FACE REGION DETECTION AND FACIAL FEATURE EXTRACTION

The possible face candidates with a highness value are passed on to the second stage. The functions of the second stage are to verify whether the candidates are human faces or not, and to extract the respective facial features in the face region. The verification process is based on the characteristics of the projected face images At this stage, the symmetry of a face candidate is measured. As every face region is normalized for the shirring select and the illumination select, the difference between the left half and the right half of a face region should be small due to its symmetry. In our method, the size of a face region is normalized to 2831, and the symmetrical measure is calculated as follows:

$$T_S = \frac{1}{434}\sum_{y=0}^{30}\sum_{x=0}^{13}|f(x,y) - f(27-x,y)|,$$



The bottom window, the mouth corner can be detected based on two assumptions; the mouth corners are close to the horizontal position of the corresponding iris and the gray-level intensity changes significantly at the mouth corner. Fig. (a) Illustrates the x-projection and the determination of the detected mouth corners. The detection result for the respective facial features is shown in Fig. Similarly, if any horizontal position of the facial features cannot be located, the candidate is assumed to be a non-facial image. Otherwise, a true face region is declared, as are the different facial features being located.

4.5 APPLY FACE DESCRIPTION

Each face is represented by a LDN histogram (LH). The LH contains fine to coarse information of an image, such as edges, spots, corners and other local texture features. Given that the histogram only encodes the occurrence of certain micro-patterns without location information, to aggregate the location information to the descriptor, we divide the face image into small regions, $\{R1. . . RN\}$, and extract a histogram Hi from each region Ri. We create the histogram, Hi , using each code as a bin, and then accumulate all the codes in the region in their respective bin by: $Hi\ (c) = \sum v, (x,y){\in}Ri\ LDN(x,y)=c\ \forall c$ Where c is a LDN code, and (x, y) is a pixel position in the region Ri , LDN(x, y) is the LDN code for the position (x, y), and v is the accumulation value—commonly the accumulation value is one. Finally, the LH is computed by concatenating those histograms: $LH = \prod H\ N\ i\ i$=1 where $\prod$ is the concatenation operation and N is the number of regions of the divided face. The spatially combined LH plays the role of a global face feature for the given face.

4.6 FACE RECOGNITION

The LH and MLH are used during the face recognition process. The objective is to compare the encoded feature vector from one person with all other candidate's feature vector with the Chi-Square dissimilarity measure. This measure between two feature vectors, $F1$and $F2$, of length N

$$\left|\chi^2\ (F_1, F_2)\ = \sum_{i=1}^{N}\frac{(F_1(i) - F_2(i))^2}{F_1(i) + F_2(i)}\right|$$

The corresponding face of the feature vector with the lowest measured value indicates the match found.

4.7 EXPRESSION RECOGNITION

We perform the facial expression recognition by using a Support Vector Machine (SVM) to evaluate the performance of the proposed method. SVM is a supervised machine learning technique that implicitly maps the data into a higher dimensional feature space. Consequently, it finds a linear hyper plane, with a maximal margin, to separate the data in different classes in this higher dimensional space. Given a training set of M labeled examples $T = \{(xi , yi)|\ i = 1, . . . , M\}$,where $xi \in \mathbb{R}n$ and $yi \in \{-1, 1\}$, the test data is classified by: $f(x) = sign\ (\sum \alpha iyiK(xi , x) + b\ M\ i$=1) where αi are Lagrange multipliers of dual optimization problem, b is a bias, and K(·, ·) is a kernel function. Note that SVM allows domain-specific selection of the kernel function. Although many kernels have been proposed, the most frequently used kernel functions are the linear, polynomial, and Radial Basis Function (RBF) kernels. Given that SVM makes binary decisions, multi-class classification can be achieved by adopting the one-against-one or one-against-all techniques. In our work, we opt for one- against-one technique, which constructs $k(k-1)$ classifiers, that are trained with data from two classes. We perform a grid-search on the hyper parameters in a 10-fold cross validation scheme for parameter selection, as suggested by Hsu et al. The parameter setting producing the best cross validation accuracy was picked.

4.8 PERFORMANCE COMPARISON

We performed several experiments to evaluate the performance of the proposed coding scheme for face recognition and expression classification. We analyzed the former under expression, time lapse, pose, and illumination variation. Also, we tested the proposed code for expression recognition with six and seven expressions.

V CONCLUSION & FUTURE WORK

5.1 CONCLUSION

Regarding the length of the proposed descriptor, the basic LDN has 56 different values, and the length of the final descriptor will be a multiple of this length. Consequently, LDNK has a length of 56, and the LDNG codes have a length of 56 n, where n is the number of sigma used (in our experiments we set n = 3). Note that similar methods have descriptors with greater lengths. For example, the basic length of: LBP (in the uniform case) is 59, LDiP is 56, LDeP is 1024, LPQ is 256, LTP (coded as two uniform LBP codes) is 128, and general LTP is 38.However, multi-scale codes, like HGPP, have huge lengths, as the global version (GGPP) length is 256 ns , and the local version (LGPP) length is 256 ns no (where ns = 5 is the number of scales, and no = 8 is the number of orientations). Furthermore, HGPP is a combination of the local and global versions, which will combine its lengths (note that the use of real and imaginary values wills double the length). Due to the length of the HGPP descriptor, we will not compare against it. Additionally, all these lengths should be multiplied by the grid size. In comparison, our multi-scale descriptor is extremely compact, and the single scale is more compact than other descriptors.

5.2 FUTURE ENHANCEMENT

In the future, we plan to improve processing speed and accuracy of the algorithm. Furthermore, we plan to apply the algorithm to movies and to apply an automatic detection, whether an image is low DOF or not.

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