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Facial Recognition Using Curvilinear Shape Descriptors

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Abstract: The importance of shape as a tool for analysis and classification has led to its study in many diverse fields of science and engineering. In this research, face recognition problem is treated as a 3D shape recognition problem of a free form curved surface. The proposed approach is based on the configural properties of the face that are reflected in the surface structure of the face. Filtering and normalizing techniques are applied to reduce the effect of quantization and also to smooth the curvature. The new-fangled algorithm is introduced to recognize and locate points of local maxima from the smooth curvature and also to reduce dominant points in order to reinforce the efficiency of the face recognizer. ART neural network (Adaptive Resonance Theory) is employed to match the shape of the test image with that of the reference shape stored in the database to discriminate the identity of the input. Experimental results show that the suggested algorithm can extract the shape descriptors of the face with estimable precision and the extorted contour are effectual to enhance face recognition. A reduction of the dominant points is also desirable to augment the competence of the face recognizer, which is comprehended in this algorithm.

Key words: Face recognition, filtering, normalizing, shape descriptors, ART neural network

INTRODUCTION

Visual information is becoming a major method of communication in modern age. Among all aspects underlying visual information, the shape of the object plays a special role. Shape perception and shape understanding have been extensively used to recognize objects in early studies. Identifying high curvature points that are rich in information content, of the objects and linking them by line segments helped a human observer for easier recognition of the objects (Takacs, 1998). This idea has been the preamble for most of the researchers in the domain of shape.

Psychological studies have uncovered that human faces can also be categorized as it contains vital information. A measurement of a facial surface furnishes information about its shape (Samir *et al*., 2006), feature (Sadr *et al*., 2003) and texture (Ahonen *et al*., 2006). Generally all the above said characteristics are used together for facial recognition, but the scope of this study is restricted to the analysis of shapes and their contribution towards recognition.

Recognition of a face by its shape is the process of comparing and recognizing faces by analyzing the shapes of the surface structure of the face. The deep structure of the face that comprises the bone and cartilage of the face, portrays unique characteristics for divergent face. The shape of the jaw, nose, upper cheek and forehead reveal the structure of the underlying bone and the overlying skin reflects faithfully the curvature of these bones.

The face recognition problem considered in this study consists of three major modules namely, data acquisition, shape representation and shape matching. A specific definition of the region to be explored is the first hypothesis to be dealt with and is elucidated in data acquisition from which the surface properties is extorted and exemplified. Given an appropriate representation scheme, the shape of a face might yield such secrets like the age, sex, race, emotions and identity of the individual. The rich semantic nature of contours makes them widely employed as shape descriptors. A novel method is instigated to extract the forehead, cheek, nose and jaw contour using the maximum curvature on the face surface. This facilitates recognition despite changes in hairstyle, skin tone and other changes in surface structure.

Finally the shape contours is applied into the matching technique to predict the similarity between the input image and the trained images. If differences in facial shapes between different people are larger, then a simple recognition procedure, such as pattern matching, can do well even if some noise is present. The organization of this study is shown in Fig. 1.

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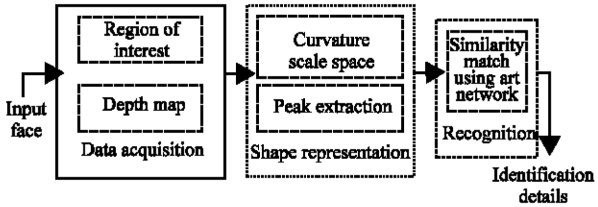

Fig. 1: Research description

DATA ACQUISITION

Many face recognition techniques have been developed for quite some time and an exhaustive survey of the same is presented in Chellappa *et al.* (1995). At present the challenge before the research community is to try and evolve a mechanism that is simple, less time consuming and highly accurate for shape recognition, since there is every likelihood that the face image may be affected by factors like change of pose, facial expression and condition of illumination. As a first step the depth map of human face is acquired, which provide a rich set of depth and surface information.

Determining the ROI: Detecting faces automatically either from the intensity or color images is a crucial task in many applications such as face recognition, facial tracking and video processing. The proposed method employs skin color segmentation to segment the skin region (Kapur, 1997) which is then processed in the YCrCb color space for determining the location of the eye (Hsu *et al.*, 2002). The YCbCr color space enables a robust detection of dark and light skin tone colors, due to its perceptual uniformity and video compression standards. Binary morphological operations are then applied to the resulting eye map to suppress the other facial areas. Finally a face score is computed from the eyemap using Anthropometric statistics (Farkas, 1994).

Face anthropometrics, the science dedicated to the measurement of the human face, states that the facial features are proportional to one another and the location of all features can be easily computed by just locating one feature distance. Thus the face score can be easily computed using the dimension of the region enclosing the eye (i.e.)

$$H_{face} = 1.8\ d_{eye\,;}\ H_{eye} = 1/3\ H_{face\,;}$$

The result of applying the above proportionality creates the basic outline of the face that segments the candidate region from the other skin regions.

Depth map: The local geometry features of the surface can provide pose independent information, although many features are too sensitive to noise. The local structure of an image can be represented in a stable and robust manner by the output of Gaussian Seperable Steerable filters. Freemam and Adelson (1991) proves that for a certain class of function, rotated copies can be synthesized by taking linear combination of a small set of basis functions. The choice of interest is the Gaussian, which is optimally localized in the sense of the uncertainty principles (Jacoh and Unser, 2004). Then given a better normalization factor, the Gaussian function satisfies

$$G = G\,(.\,,\sigma) = \frac{1}{2\Pi}\ \exp\ \frac{-x^2 + y^2}{2\sigma^2}$$

an amazing number of mathematical properties that describe a vast variety of physical and probabilistic phenomena.

Subsequently, the depth map of the image is got from the filtered image as (x, y, z(x, y)) where the intensity of each point (x, y) is the depth z(x, y) (Francis *et al.*, 2003). This constructs the range image for global segmentation of the face using the signs of Mean and Gaussian derivative estimated from the depth map. Accordingly a computationally proficient local optimization for shape adaptable feature recognition is recommended.

SURFACE-TO-SHAPE

One of the important steps in computational shape analysis is the representation of shape that refers to the process of presenting shape in a form suitable for storage and/or analysis. Shape is represented by an ordered sequence of line segments with control points as vertex points (Liu *et al.*, 1998). Finding good shape descriptors for the appearance of local facial regions is an open issue and has been widely discussed for at least a decade. Chain coding (Freemam and Davis, 1977), Fourier descriptors (Persoon and Fu, 1986), invariant moments (Zakaria *et al.*, 1987), auto regressive model (Dubios and Galanz, 1986) and syntactic approaches (Chen and Su, 1986) are all well known methods of shape representation.

Shape descriptors should be invariant to geometric transformations, robust to noise, meaningful to matching algorithm robust to occlusions and computationally feasible. Universal descriptors are changes-to-design, projector-invariant descriptors that are easy to compute and must have high extra-class variance (i.e. between different people) and low intra-class variance (with respect to aging of the subjects). Descriptors are also sorted according to whether they are based on boundary information (external description) or the information from surface region (internal description).

Therefore, a very careful choice of descriptors resulting from detailed analysis of the shape recognition problem must precede any implementation and their preference must be based on its ability to describe global surface properties like size, boundary, curvature etc., (Moreno *et al*., 2003). The basic principle is that the distinct boundary information corresponds to the convex region of the range image from which the points of local maxima determined are assigned as control points. *Contours*, formed by a sequence of control points, are good shape descriptor and are also referred, as Profiles or Silhouettes or Outlines.

Surface stimuli: Curvature, a scale-dependent quality, is the key to compute shape descriptors (Reeger *et al*., 2004). The curvature scale space of the contour is derived using the Gaussian derivatives. It has been shown by several authors (Stokely and Wu, 1992; Francis *et al*., 2003; Lee and Shim, 2004) that under specific constraints, the Gaussian derivative form a unique operator for representing an image. The images are then filtered with the Gaussian derivatives and at each pixel the surface curvature is computed. The Gaussian curvature (K) and Mean curvature (M) are calculated as

$$K = \frac{f_{xx} f_{yy} - f_{xy}^2}{\sqrt{(1 + f_x^2 + f_y^2)^2}}$$

$$H = \frac{f_{xx}\,(1 + f_y^2) + f_{yy}\,(1 + f_x^2) - 2\, f_x\, f_y\, f_{xy}}{2\,(1 + f_x^2 + f_y^2)^{3/2}}$$

$$\text{Where } fx = \frac{\partial f}{\partial x},\ f_y = \frac{\partial f}{\partial y},\ f_{xx} = \frac{\partial f}{\partial x^2},\ f_{yy} = \frac{\partial f}{\partial y^2},\ f_{xy} = \frac{\partial f}{\partial x \partial y}$$

If $K > 0$ and $H < 0$, the point (x, y) or surface is peak surface. If $K > 0$ and $H > 0$, the point (x, y) or surface is pit surface (Tanaka and Ikeda, 1996). The high curvature values of these peak regions provide compact description for the face surface shape and are used as robust and stable contours for face recognition.

Surface-to-silhouettes: The local maximum curvature (contour) is a widely discussed problem, where the outcome and accuracy of the ensuing shape analysis is heavily dependent on the methodology used for extraction. The image normalization and curvature representation from the depth maps makes this process easy. Since the contour is planar, one can utilize 2D image analysis to perform contour extraction and avoid 3D issues (Samir *et al*., 2006). Range images of facial surfaces are mostly smooth and non-flat, with well-defined level contours with minimal range discontinuity around the regions pertaining to jaw and eye (Samir *et al*., 2006; Lee and Milios, 1990).

The extraction of contour is a straightforward approach. For an observed contour, denoting a peak region, the representation of the shape of a face can be easily removed employing a modified Raster Scan Boundary Extraction Technique (Metilda and Santhanam, 2007). The fundamental methodology is to track the contour, pixel by pixel from the starting point along the proceeding direction. All the course of the contour is to be thoroughly examined in its neighborhood, in contrary to the facial feature extraction described in Metilda and Santhanam (2007).

The general outline of the algorithm can be summarized as follows (Fig. 2).

Input: Points of local maxima relating to the peak region.

Extraction: Perform contour following, in the proceeding direction. Locate the appropriate initial points of the entrant contour for extraction. A 4×4 neighborhood with top left point selected as the salient pixel is used to locate whether the pixel lies in the candidate contour. The run length of the boundary is employed to determine the direction of the contour. It can be easily empirical that the direction of the curve ensues horizontally direction when the total run length breadthwise is enormous and if it is immense depthwise, then the contour is concluded to evolve vertically. Otherwise, the curve is appraised roughly diagonal and is pronounced to be a bent curve.

Filtering: The contour covering the forehead, nose and jaw area are hypothetically longest resulting in the suppression of other contour in the peak surface. A measurement of the candidate contour using Euclidean distance will serve as a metric to explore the contour. If a contour instigate at a noisy point, the length of the contour will be diminutive. A small contour representing redundant feature points will not be able to implement the dissimilarity in the wider scale in contrast to an elongated contour and thus can be eradicated.

Smoothing: After selecting the contour that signify the shape of the face, ‘filling gaps’ and ‘removing spikes’ are subsequently carried out to shun discontinuity.

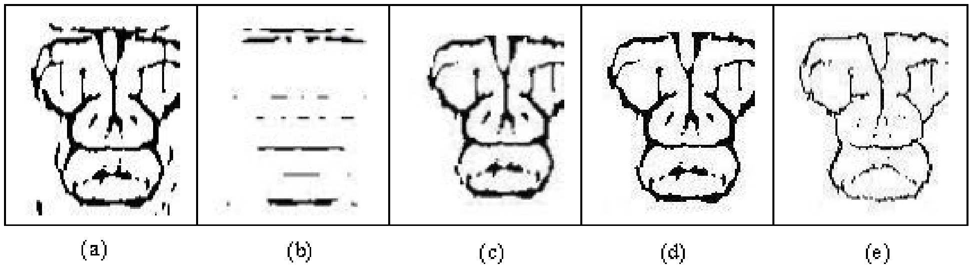

Fig. 2: (a) Peak region (b) and (c) Contour extraction (d) Removing noise and filling of holes (e) Skeletonization

Gap: Using a connection technique unravels this intricacy. If the neighborhood of the inspection point in the candidate contour is busted, an average between the coordinates of the consecutive contour points are found and filled such that binary openings with 2 pixels are closed within the bounds.

Spikes: An outlier removal methodology can be used to eliminate extraneous data points. High-density data sets will often comprise outliers that may not reflect the actual geometry of the surface. These might occur due to the filtering process of the noisy input. In many cases, it is useful to apply mathematical methods to remove these data points rather than re-measuring the components. Several methods have been suggested in the literature to alleviate this problem. One of the approaches, averaged high-to-low deviation method, has been used to quantify the deviations with respect to the ideal geometry. This applies a simple measure of the data points in its neighborhood to smooth out the deviation.

Thinning: The output of the previous step is a broad contour that portrays the shape of the face surface. A skeleton construction can be used to acquire an exact shape descriptor. There are many fundamental methods to skeleton construction of which thinning is an iterative removal of region boundary pixels. It repeatedly removes the boundary elements until a pixel set with maximum thickness of one is found. Also sufficient care must be taken to ensure the skeleton connectivity.

Output: The outcome of the algorithm, namely the feature contours, becomes the input for the recognition phase.

FIND OR INCLUDE

Once the complete set of contour is extracted, the subsequent problem of recognition of the shape of a given input becomes much simpler. The objective of developing a recognition procedure for a shape pattern is that 'given a shape pattern of unknown personality, one may wish to identify that the given pattern is identical to a prototype shape pattern in the database'. The high correspondence between the input pattern and the matched pattern in the database then reveals the identity of the person.

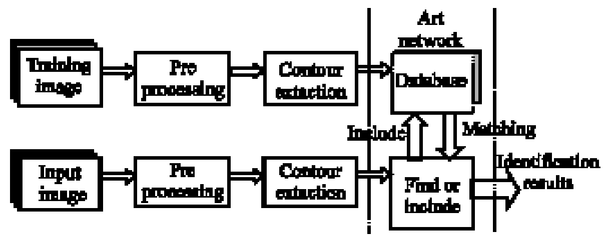

Fig. 3: Block diagram of face recognition using curvilinear facial shape descriptors

Find or Include is a recognition model based on the Artificial Neural Network (ANN) consisting of simple elements (neurons) and bounds between their outputs (Synapses). The procedure for construction is as follows (Fig. 3):

- A user-defined database is created by sending the contour of the training images as input to Adaptive Resonance Theory (ART) network.
- The contour of the entrant image is applied as input to ART, for finding a possible match with the template database.
- If there is no match, the contour of the identity is added to the database.

The architecture of ART designed by Carpenter (1997) self organizes and stabilizes its recognition codes in response to arbitrarily complex binary input pattern. As the learning proceeds, interaction between inputs and the database generates a new steady state. These steady states are formed as the system discovers and learns feature patterns that represent shape.

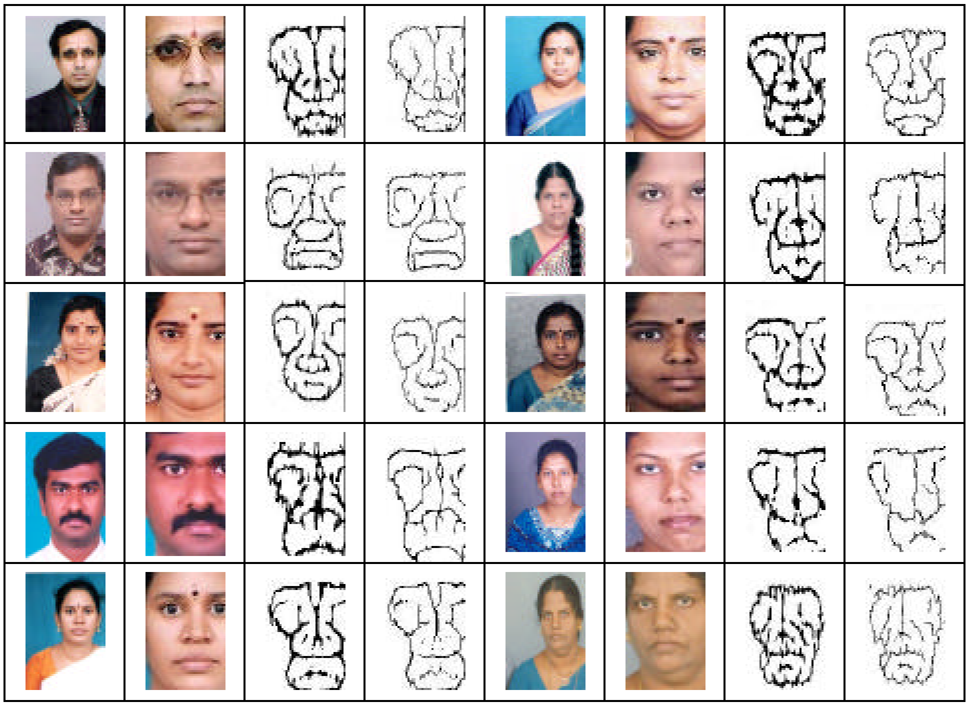

Fig. 4: Extracts from database creation

An ART system is capable of plasticity in order to learn about significant new events and it also remains stable in response to irrelevant inputs (Carpenter and Grossberg, 1987). Multiple interacting memory systems are needed to monitor and adaptively react to the novelty of events. Within an ART, interaction between two functionally complementary subsystems is needed to process familiar and unfamiliar identities. One subsystem is to establish even more precise internal representative of familiar identities. This mechanism plays a major role in self-stabilizing the learning of an existing identity. Another system is to create new identities for unfamiliar pattern.

Unlike other recognition models, this model can deal with arbitrary combination of binary input patterns. The model is capable of storing arbitrarily many identities in response to its input pattern. As a consequence, the matching and recognition of identities using face surface shape has been reduced to Find or Include using an ART network.

PERFORMANCE ANALYSIS

The performance of the proposed algorithm is tested by means of a database, consisting of 25 reference face surface shapes from 18 personalities, constructed by means of applying the preprocessing steps and the modified Raster Scan Boundary Extraction algorithm elucidated in this study (Fig. 4). That is, the contour vector of the different images, describing the shape of face surface is extorted to construct a database reducing the problem of face recognition to the study of similarity and disparity between face contours.

Thereafter the find or include is performed as demonstrated in this study. The precise correspondence between the contour in the database and the input image is determined using the ART network where a 'Find' indicates the identity of the person while a no match tends to 'Include' the contour of the new identity in the database.

As opposed to other face recognition techniques, a reduction in the number of points representing the shape of the face is realized using the Raster Scan Boundary Extraction technique explained in this study. From a shape theoretic point of view, the shape of the contour and its relative location are quantitative measures to account the performance results of the extraction algorithm. The differences in facial shapes between different people were noticeably larger (Fig. 5) and for this reason a recognition rate of 96% is evident using the shape-matching algorithm with a vigilance parameter value of 0.92.

Vigilance parameter	0.97	0.95	0.92
Recognition rate	93%	94%	96%

Fig. 5: Influence of Vigilance parameter on recognition rate

The noisy contours (especially in the check and jaw) of the face add a significant contribution in the loss of accuracy, predicted due to the aging of the subject. Occlusions are another hard problem in shape recognition that contributes to fault rates. The local maximum curvatures, which are the shape descriptors or the bounding curves of the face surface shape, are found to be less affected by translation and scaling. Another observation is that maximum curvatures are subject to less change between facial expressions. This contributes to the robustness of face recognition system based on shape. Rotation however may cause some distortion of the discrete shape.

CONCLUSION

A novel and proficient facial shape representation algorithm is presented in this research. The experimental results clearly prove that the extraction method is effectual in yielding high recognition rate. Considering that a coarse sampling of a facial surface has been performed completely ignoring the feature descriptors and a texture detail, the recognition rate is quite significant. Accordingly shape descriptors describe the appearance of the shape and the combination encodes the global geometry of a face.

The techniques described are intricate in their own spheres and require fine-tuning. Standardized curvature function can further smooth the curves to augment the recognition rate and an alternative bending energy functions can be intended to perk up the extraction technique. Also, requisites on shapes of faces can be made to betray interesting secrets such as age, sex, race, etc., are worth exploring.

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