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# Face Recognition Using Curvilinear Feature Signatures

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**Abstract:** Face recognition is a difficult visual representation in large part because it requires differentiation among human faces, which vary subtly from each other. The objective of this study, is to use the information that outlines the facial features using the curvature scale space. Pointwise curvatures, which are 'Natural Signatures', of facial features are well suited for facial feature recognition. The accuracy of such feature-based recognition is very high because the value of curvature at a point on the surface is viewpoint invariant. A novel method for extraction of the facial feature signatures from the curvature map of the human face is presented in this study. Comparison between two faces is made on their relationship in feature face using ART neural network. Satisfactory results using diverse probe data prove that curvilinear facial feature signatures provide vital clues in distinguishing and identifying human face.

**Key words:** Face recognition, range data, mean and Gaussian curvatures, anthropometrics, ART neural network

## INTRODUCTION

A Biometric system is a pattern recognition system that determines the authenticity of an individual using some physical or behavior features. The requirement for reliable personal identification in computerized access control has resulted in an increased interest in biometrics. Biometrics being investigated includes Fingerprints, Face recognition, Iris, Speech and Signature. In these, face recognition is one of the most difficult visual tasks because it requires differentiating among large number of complex natural objects, which consist of free-formed curved surface and have similar structure (Chellappa *et al*., 1995). Many face recognition techniques have been developed over the past few years. Previous recognition systems measure facial characteristics from photographs of a face into nine geometric parameters of distance between key points of the face (Kaya and Kobayashi, 1972). Building on this, Kanade (1977) represents the face by 16 parameters. The parameters are composed of eleven distance ratio and a combination of angle and curvature.

The recognition system deployed in this study exploit range images of faces, unlike the other conventional methods. Range images gained much attention in computer vision area for the human face recognition. Range data provide explicit geometrical information about the shape of visible surfaces (Lee and Milios, 1990). Gordon (1992a, b) presented a detail study of range images in human face recognition based on depth and face surface curvature features. Surface curvatures are local features that are invariant to all affined transformation. Past research (Ernest and Shang, 1992; Franics *et al*., 2003; Hiromi and Masaki, 1996; Yeung and Shim, 2004) has shown that surface may be classified by observing the sign of the Mean and Gaussian curvature. They are intrinsic surface properties that have played important roles in both characterizing and recognizing curved surfaces. Thus if such curvatures could be reliable and constantly calculated, they could be ideal for feature based recognition.

The approach adopted in this research is based on two hypotheses, namely the segmentation of the visual exemplars of the face and judging the uniqueness of the individual with a known identity. The first hypothesis is comprehended by a raster scheme that relent a depiction of the facial features such as the eye, nose, lips, and chin extracted from the curvature maps derived from the computation of the depth maps. Secondly the specified task, to distinctively recognize the individual by approximating the similarity of faces as a whole, is accomplished by querying the database using the differential features and then letting the recognition system built on the framework of ART neural network to decide either to ascertain the identity of the individual or to include the same in the database.

Data acquisition, segmentation based on the signs of the Mean and Gaussian curvature, isolating regions of

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pronounced curvature (Feature extraction) which determines the discriminating power in data set and Recognition procedure to recognize and identify have been the tasks for the accomplishment of the hypothesis. The main issue underlining most of the previous work in this category is the measure of significance and the automatic determination of the region of support. Teh and Chin (1989) argued that the detection of dominant points relies primarily on the precise determination of the region of support.

## PREPROCESSING STEPS

This study details the preprocessing steps (Fig. 1) for determining a depth map of a face. The extraction of feature points relies not only on the accuracy of measurements, but also on the precise determination of the region of support (Majed and Pepe, 2003). Choosing a large region of support will smooth out the feature of a curve. Choosing a small region of support will produce too many redundant feature points. So selecting a suitable region of support is important in the recognition problem.

**Region of interest:** Detecting faces is a crucial step, which can be viewed as a two-class detection problem. The first detects regions, which are likely to contain human skin in color images (Jay, 1997). The skin detection is performed using a modified skin filter, which relies on color and texture information. The image is converted from RGB color space to IRgBy color space and a combination of thresholding and mathematical morphology are used to extract the skin region. The algorithm enables a detection of dark and light skin tone color.

The segmented skin region includes the neck region and some noise. The next step locates the eye boundary using the YCbCr color space (Rein *et al.*, 2002) and segments the face region using distance of the eye. An eyemap using the chrominance component and the luminance component is constructed by an AND operation. The resulting eyemap is then dilated, masked and normalized to brighten both the eye regions and suppress other facial areas.

Anthropometrics, a theory that states that the facial features are proportional to one another, can be used to calculate the location of all the features by locating just one facial feature distance (Farkas, 1994). It states that the height of the face is found by using the eye region.

$$H_{Eye} = 1/3\ H_{Face}; \qquad H_{Face} = 1.8\ D_{Eye}$$

Using the above, the dimension of the entrant face region is calculated and segmented to determine the region of interest.

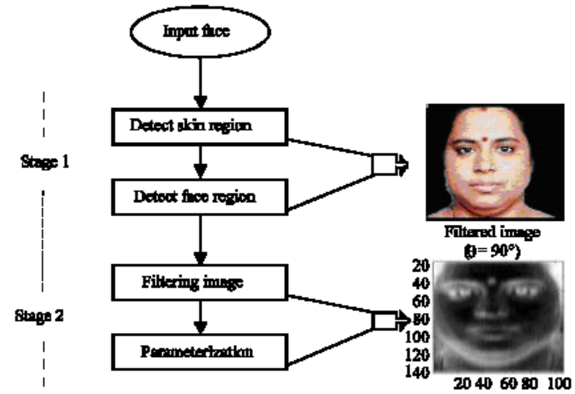


Fig. 1: Preprocessing steps

**Face representation:** The filtered face is next preprocessed using Gaussian Steerable filter. Differential approaches to rotation independent feature detection are provided by the elegant work of Freeman and Adelson (1991), Mathews and Michael (2004) on Steerable filters. The underlying principle to generate the rotated version of a filter from a suitable linear combination of basis filter, provide the best compromise in the terms of noise, false detection and localization of feature points. Also the second order derivative information used to represent curvature will be stable if instead of using just finite differences; they are computed by filtering an image with normalized Gaussian derivative function (Gordon, 1992):

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

Derivative information is most accurately acquired from digital data through an analytical surface representation. As the last step of preprocessing, since the intensity of each point (x, y) is the depth z(x, y) of that point, the face surface can be easily parameterized by (x, y, z(x, y)). This approach rather provides satisfactory results to determine the surface characteristics (Ken, 1990; Richard *et al.*, 1996).

## EXTRACTION OF DIFFERENTIAL FEATURES FROM DEPTH MAPS

A novel method for extraction of the facial features from the curvature map of the human face is presented in this study. The preprocessing step allows to robustly obtaining the position of the features in an image with sub-pixel accuracy. Feature points play a very important role in the accuracy of recognition. For a facial features to be easily tracked it should be independent of translation, rotation and scale of objects. The distinction between the features of two faces must have different shapes and the required computational time should not only be short but also storage capacity required should be small. The features are also required to satisfy the continuity property for a precise and smooth tracking.

The new extraction method is designed to conserve these properties of the set of features-nose, eyes and lips in the process of segmentation and use their relative region and shape to recognize a person. Distinct facial features can be represented explicitly using geometries of the surface. These features under apprehension correspond to pit regions (minimum curvature) of the range image of a face (Francis *et al*., 2003; Gordon, 1992).

**Computing curvature from range data:** The notion of curvature for continuous curves is a defined concept from differential geometry. Derivatives capture useful statistical information about the image. The first derivative represents the gradient or edginess of the intensity and the second derivative can be used to represent curvature characteristics (bars, blobs and so on) (Ernest and Shang, 1992; Francis *et al*., 2003; Hiromi and Masaki, 1996; Lee and Milios, 1990).

The Gaussian curvature K and the Mean curvature H used for surface characterization are given by

$$K = \frac{g_{uv}\, g_{vv} - g_{uv}^2}{(1 + g_u^2 + g_v^2)^2}$$

$$H = \frac{g_{uu}\,(1 + g_v^2) + g_{vv}\,(1 + g_u^2) - 2\, g_u\, g_v\, g_{uv}}{2\,(1 + g_u^2 + g_v^2)^{3/2}}$$

These curvatures are viewpoint invariant under rigid transformation. Smooth surfaces are locally characterized by them and are classified into surface types using a combination of their signs (Table 1). These curvatures are local to surface regions and are stable under occlusions.

**Raster scan boundary extraction technique:** After computing local surface curvature accurately and segmenting range image into several surface regions with similar surface types, a segmented facial surface pertaining to the pit region called the facial feature curves or Facial Feature Signatures (FFS) are isolated. A new extraction method, the Raster Scan Boundary Extraction Technique is used to extort the FFS pertaining to the facial features (eye, nose and lips) for the recognition procedure.

The raster scan mechanism applies the curve-following to obtain sequential boundary points. The top/bottom left point of the pit vector is selected as the starting point and the direction of search is applied depending on the feature extracted. A 4x4 neighborhood of pixels is considered at each point of inspection to determine the direction in which the curve proceeds. When a dead end is reached, the algorithm will backtrack along the presumed points until a proper part of the curve is tracked. Since the extracted features are in general roughly either horizontal or vertical, the other directions of the neighborhood are not considered.

Table 1: Surface interpretation of Gaussian curvature (K) and Mean curvature (H) signs

| | K > 0 | K = 0 | K < 0 |
|---|---|---|---|
| H < 0 | Peak | Ridge | Saddle ridge |
| H = 0 | None | Plane | Minimal surface |
| H > 0 | Pit | Valley | Saddle valley |

The eye region is explored by adopting a breadthwise propagation. Connection techniques based on the neighborhood has been used to reckon the fact that small gap will be ensuing from the extraction (especially in the eye socket region). If the neighborhood of the salient point is broken, an average between the coordinates of the successive point is found and filled.

$$P_{i+1} = (P_i + P_{i+2})/2;$$

A similar approach is also used to extract the nose curve. Depthwise search propagation is carried out to generate the characteristic curve. To determine the ‘U’ shape of the nose, the disconnections (often horizontally) are completed by a similar connection technique as the eye. The lip is a clogged curve, which is extracted by a combination of depth and breadth search propagation. A binary opening with 2 pixels wide is closed within the bounds by the same connection technique described earlier.

The facial curves pertaining to the entrant region are the longest and are employed to eliminate other curves and noise that are generated in the process of extraction. A count on the number of pixels that make up the descriptive facial curves is saved to decide the curve. Thus the curves with maximum pixels are retained for further processing. This course of action to extract the facial curves for matching process in the recognition phase makes it easy to sieve out a great measure of noise present in the segmented range image.

But the ensuing curves need to be skeletonized for more precise results. At this point one cannot erode these curves, since some of the disconnections could still remain afterwards. Consequently a binary skeleton transformation can be applied. There are four basic approaches to skeleton construction.

- Thinning-iterative removal of region boundary pixel.
- Wave propagation from the boundary.

- Detection of local maxima in the distance-transformed image of the region.
- Analytical method.

A thinning procedure that repeatedly removes boundary elements until a pixel set with maximum thickness of one or two is found is used in this extraction technique. The previously obtained facial curves are progressively scanned starting from their boundary pixels. The neighborhood is constrained to see if the curve is continuing at the pixel horizontally or vertically. Accordingly the pixels in the neighborhood are removed, such that it does not modify the homotopy of the curve. This approach yields a shaded curve from the previously extracted thick curve. The process is iterated to generate a 1-pixel thick curve akin to a cartoon sketch of the face features.

**Algorithm:** Raster scan boundary extraction technique.
**Input:** The planar curves of the segmented pit region of the face surface.

**Step 1:** Delineate a raster scan boundary mechanism to extort the FFS of the apprehensive feature curves.

- Define a breadthwise propagation for extracting the eye curve
- Define a depthwise propagation for extracting the nose curve
- Define a combination of both depth and breadthwise mechanism to extract the lip curve.

**Step 2:** Resolve the binary opening with 2 pixels wide both horizontally and vertically and reduce it using the connection technique.

**Step 3:** Filter an immense measure of noise using the longest curvature attribute of the candidate curves.

**Step 4:** Apply the skeleton transformation to the thick feature curves generated.
**Output:** Generates a cartoon sketch of the FFS.

## MATCHING AND RECOGNITION USING ART NETWORK

Once the feature curves are extracted, the residual problem is to compare curve correspondence using their relative location and shapes. To establish correspondence between features of two faces a matching algorithm that only allows pairs that have mutually consistent spatial locations in the domain of the range images is applied.

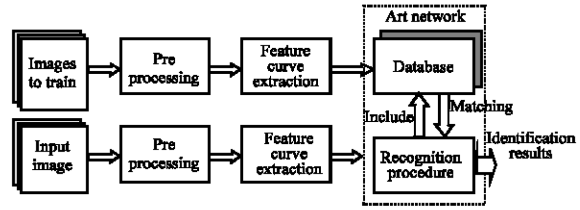


Fig. 2: Block diagram of face recognition using curvilinear feature signature

Each face in both input image and the model database is represented as FFS, extracted by the new boundary extraction procedure (Fig. 2).

Matching individual faces and then recognizing by evaluating the similarity among others is carried out using an Adaptive Resonance Theory (ART) neural network. ART feature winner-take-all competitive activation, which permits fast learning and stable coding but which causes category proliferation with noisy inputs. Its architecture is neural network that self-organize stable recognition codes in real time, in response to arbitrary sequences of input patterns. The basic principles of ART are introduced by Carpenter (Gail, 1987, 1997). ART networks self-organize stable recognition, categories in response to arbitrary sequences of analog (gray-scale, continuous-valued) input patterns, as well as binary input patterns. In ART models, a vigilance parameter '$\rho$' establishes a network matching criterion that, if not met, leads to category reset and search. The processing cycle of bottom-up adaptive filtering, code (or hypothesis) selection, read-out of a top down learned expectation, matching, and code reset shows that, within an ART system, adaptive pattern recognition is a special case of the more general cognitive process of discovering, testing, searching, learning, and recognizing hypotheses (Gail, 1991).

The central feature of the ART systems is a pattern matching process that compares the current input with a learned expectation provided in the database. ART matching leads either to a resonant state, which focuses attention and triggers learning, or to a self-regulating parallel memory search, which eventually leads to a resonant state, unless the input is recognized. If the search ends at a new identity, the feature curves are stored. This match-based learning process is the criteria for selecting ART network for matching and recognition of the facial feature curves in this paper. It validates the correspondences, presenting the maxima of matched points extracted from the 2 images. Such correspondence allows a very accurate point to point matching.

## EXPERIMENTAL RESULTS

In this study, experimental results from computing of the facial feature curves and identifying the personality are elucidated. The facial signs derived from 3D net were used to acquire fine-grained discriminating indices for face classification and were found to conserve the visual information.

**Feature extraction:** First a set of preprocessing steps explained in this study is applied to the 25 frontal images to create a database, of which 7 individuals have more than 1 image. Results confirm that determining the precise face region reduces the computational time for the extraction of facial curves and reduces the matching scale space. Filtering and parametric surface model representation is effective for the computation of precise surface properties from which feature curves can be extracted with high continuities. Subsequently, the surface properties such as the Mean and Gaussian curvatures are determined with high significance to locate the pit regions using their signs.

The exactness of face representation using depthmap helps to segment intuitive pit region with most errors, around the edge of the face image, eliminated using suitable techniques. The facial curves also referred, as Facial Feature Signatures (FFS) are extorted using the new raster scheme based on curve-following as designed in this study (Fig. 3). These FFS were not only unique and robust for every individual but also continuous except for slight discontinuities around the eye. Minimal unwanted distortions found in the lobe of the nose were negligible, as it did not hamper the recognition rate.

The assessments on the FFS show that feature curves are unchanged with respect to different aspects of the individual. The occlusions such as spectacles only deter the eye curve to a modest level while the mustaches of male individuals have an effect on the upper segment of the lip (Fig. 4). The nose curve is found to be faintly biased by the aging of the subject and the muscle fat in the face (Fig. 5). The tolerance rate of these obstructions is small and hence they have a minor effect on the recognition of the individual.

**Recognition analysis:** Training the ART network was carried out with 75% of the images in the database created and the rest was used for testing the system. Figure 6 shows an illustration of the different steps in constructing the FFS for two face images of a person with a disparity of atleast 15 years. The matching between the two cartoon sketches of the images is obtained with a vigilance parameter value of 0.97.

The 96% recognition rate from the recognition algorithm with FFS as input is critically dependent on the accuracy of curvature estimations to obtain an accurate description of the facial feature curves. The high vigilance

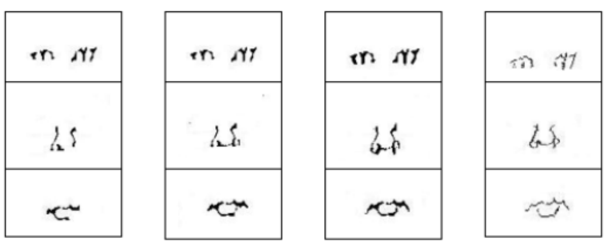

Fig. 3: (a and b) Feature extraction (c) Filling holes (d) Skeletonization

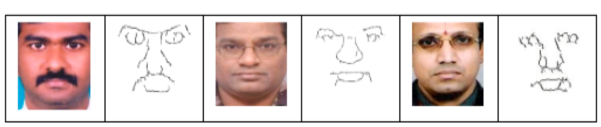

Fig. 4: Probe data with occlusions

Fig. 5: Instance of structure distortions due to aging of subject and muscle fat

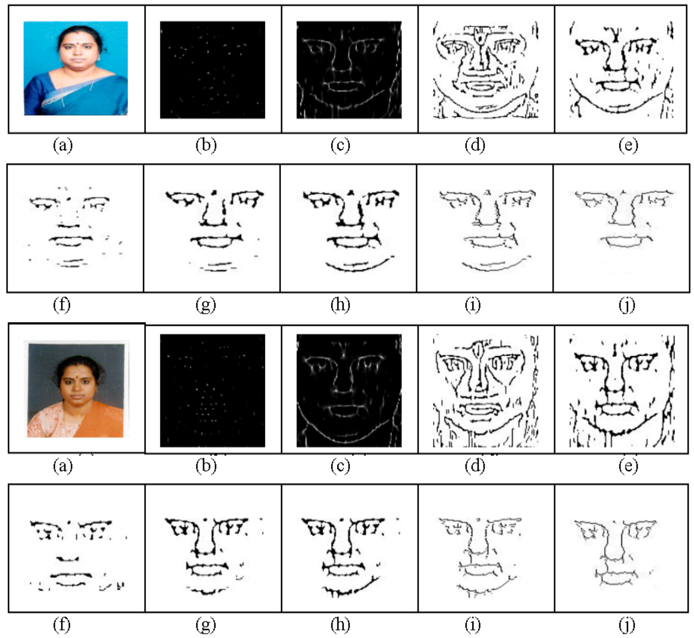


Fig. 6: (a) Input image (b) Gaussian curvature (c) Mean curvature (d) Binary image (e) Pit region (f) Breadwise extraction (g) Depthwise extraction (h) Filling holes (i) Skeletonization (j) Cartoon Sketch of the facial feature curve

| | | | |
|---|---|---|---|
| Vigilance parameter | 0.97 | 0.95 | 0.92 |
| Recognition rate | 96% | 93% | 85% |

Fig. 7: Influence of vigilance parameter on recognition rate

rate shows that extremely reliable discrimination between numerous faces is achieved only by small displacement of face features (Fig. 7) while the failure rates were primarily due to the occlusions and aging of the subject.

## CONCLUSION

As the complexity of the surface increases so do the error in curvatures. The poor extraction of the pit region produces a very noisy curvature map; while the carefully extracted facial feature curves using raster scan technique produce intuitive FFS. Many different factors that contributed to the high successful rate are given below.

- The precise face region.
- The accuracy of face representation.
- High and continuous curvature point extraction.
- The precision of feature curves.
- Reduction in feature points for recognition.
- The selection of network for matching and recognition.

An extended surface extraction method to improve the recognition rates can be considered for future studies. The possibility of using standardized curvature function to segment the curves and the two segments with close curvature function can be said to resemble each other, is worth exploring.

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