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Yong Zhang, Sangeeta J. Kundu, Dmitry B. Goldgof, Sudeep Sarkar
Department of Computer Science & Engineering
University of South Florida
Tampa, FL 33620

Leonid V. Tsap
Advanced Communications and Signal Processing Group
Electronics Engineering Department
University of California Lawrence Livermore National Laboratory
Livermore, CA 94551

Abstract

[1] *This paper describes a face recognition method that is designed based on the consideration of anatomical and biomechanical characteristics of facial tissues. Elastic strain pattern inferred from face expression can reveal an individual's biometric signature associated with the underlying anatomical structure, and thus has the potential for face recognition. A method based on the continuum mechanics in finite element formulation is employed to compute the strain pattern. Experiments show very promising results. The proposed method is quite different from other face recognition methods and both its advantages and limitations, as well as future research for improvement are discussed.*

1 Introduction

During the past a couple of years, biometrics research has received considerable attention due to its high potential in security related applications. There exists a wide variety of biometrics techniques, some are relatively mature while other are still in their infancy. Each biometrics technique has its pros and cons, and it is not possible to find a single one that can solve all practical problems. Therefore, there is always a need for new biometrics.

Other than fingerprint, face recognition is probably the most natural (and hence a popular) biometrics because we have developed the ability to recognize faces automatically with no conscious effort. Current face recognition methods rely on visible photometric or geometric attributes that are present in intensity images. Based on large amount of research and benchmark studies [1, 8, 7], it has been recognized that those methods suffer from problems associated with following factors: (1) illumination and pose variation; (2) make-up, hairs and glasses; (3) plastic surgery; (4) face deformation during expression (dynamic face analysis in video sequence). Future face recognition methods must address those difficult issues.

We propose a new class of features (or biometrics) that is derived from the computed strain pattern exhibited during face expression. The proposed method has several advantages:

1. Elastic strain pattern is directly related to the material property of underlying facial muscles. Our hypothesis is that, if the anatomical structure of an individual face (geometry, distribution and strength of bones and muscles) is unique, then this anatomical uniqueness should be reflected in the elastic strain pattern. Strain pattern could be less sensitive to the illumination and pose changes as well as camouflage using makeup.

2. The computation of elastic strain map requires at least two frames that capture the face deformation during expression. Most face recognition methods use static images only and dynamic face expression has been considered as an adverse factor that may cause performance degradation [13]. However, a recent study by Yacoob and Davis [14] indicates that deformed face (smiling face) is more recognizable and actually increases the identification rate. We want to go one step further beyond the visible cues in face expression to recover the elastic strain pattern that might help to reveal the underlying anatomical individuality.

3. Anatomy-based physical model has been widely used in realistic facial animation and surgery simulation [6, 12, 5]. Essa and Pentland [9] proposed a physical model to represent facial motion and distinguish face expressions. They used the model to estimate visual muscle activation and to generate motion-energy templates for each expression. However, we are not aware of any study that uses physical model to compute elastic strain pattern for the purpose of face recognition. A finite element model based on continuum mechanics enables us to compute the strain map accurately.

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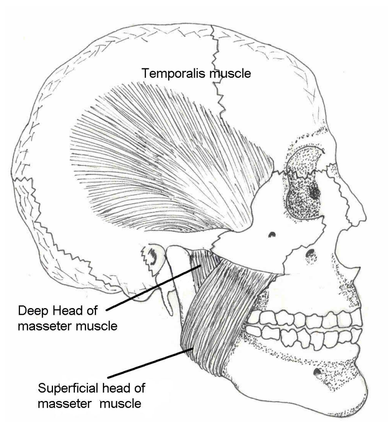


Figure 1. Illustration of masseter muscle [3].

2 Hypothesis: Face Anatomy and Muscle Biomechanics

Biometrics refers to the identification of an individual based on distinctive physiological or behavioral characteristics. In face recognition, the hypothesis is that each individual has a unique visible face pattern in terms of shape, color or texture that can be utilized for recognition. This uniqueness in visible pattern is certainly related to, and probably determined by, the uniqueness of the underlying anatomical structure and biomechanical compositions, which could also be useful for recognition, if they are measurable.

Major anatomical units of human face are: bones (skull), muscles, skin, blood vessels and nerves [3]. The use of skull measurement in identification (craniofacial analysis) and its forensic implications is well documented [4]. But it is doubtful that a practical biometrics can be derived due to the limitation of special imaging modality (X-ray is needed for skull measurement). It is also difficult to capture facial nerve patterns with current imaging technologies. The blood vessel patterns, however, has been utilized in both facial thermography and iris-retina scans with the aid of infrared camera.

Face expression is controlled by muscles and emotional states that trigger and change the muscle movements, which could be quantified by the elastic strain pattern. Elastic strain pattern computed from the observed face deformation not only reflects an individual's emotional status, but, more importantly, also reveals the intrinsic muscle properties, and therefore can be utilized for recognition. This unique strain pattern associated with an individual can remain unchanged for a long period of time, although it is reasonable to expect some variations caused by aging (loss of elastin fibers and muscle elasticity), injuries and plastic operations. The FACS (Facial Action Coding System) [2] is also based on the hypothesis that each individual has a unique facial movement and can be used for identification.

An ideal face model to compute strain pattern should incorporate all anatomical details. However, such a full-scale model would be too expensive to be realistic for face recognition. To strike a balance between modeling accuracy and computational efficiency, we have to make a compromise on what to model and how to model.

Although a whole face contains more information about an individual, it is more practical to model a portion of face whose deformation is dominated by one or a few major muscles. We choose a section that is between the cheek bone and jaw line (side view) and covered by the masseter muscle (Figure 1). The masseter muscle is a large, thick and roughly rectangular plate that is responsible for jaw action. We will model its deformation between two positions, namely a closed mouth and an open mouth.

Masseter muscle is of striated type and located just beneath the skin tissue, and its contraction has an immediate effect on skin motion. Therefore, we will not treat skin as a separate functional layer. Instead, we model the deformation of muscle and skin together as an integrated mechanical unit. This single-layer model satisfies requirements of face recognition. But two-layer model may be considered, especially for older people where the motion of muscle and aged skin are less synchronized (wrinkles).

3 Computational Method

There are four major steps in computing elastic strain pattern: (1) feature extraction and motion measurement; (2) finite element construction; (3) strain computation; (4) conversion of strain map to intensity image.

Feature Extraction and Motion Measurement We first extract salient points from intensity images and then construct a polygonal surface using the Delaunay principle. Feature extraction is based the computation of a gradient matrix within a window (w):

$$g = \begin{bmatrix} \sum^w \frac{\partial I}{\partial x}\frac{\partial I}{\partial x} & \sum^w \frac{\partial I}{\partial x}\frac{\partial I}{\partial y} \\ \sum^w \frac{\partial I}{\partial y}\frac{\partial I}{\partial x} & \sum^w \frac{\partial I}{\partial y}\frac{\partial I}{\partial y} \end{bmatrix} \qquad (1)$$

where I is image intensity and (x, y) are row and column. The first derivatives are obtained by convolving intensity image with the derivative of Gaussian filter (G): $\frac{\partial I}{\partial x} = \frac{\partial G}{\partial x} * I$, $\frac{\partial I}{\partial y} = \frac{\partial G}{\partial y} * I$. The coefficients of all pixels inside w are then summed up to produce the gradient matrix, which has two eigenvalues: $(\lambda 1, \lambda 2)$. Given a threshold T, satisfaction of condition: $\min(\lambda 1, \lambda 2) > T$, suggests that the window contains a feature point. More details about the method can be found in [10].

Due to the nonrigid nature of face deformation, we presently establish correspondence between two frames manually to ensure the quality of displacement vector. The displacement data will be used in the finite element model to specify the Dirichlet boundary condition. This manual processing is not new in early face recognition research where eyes and other facial features are manually located (FERET test [7]). Future work will use an automated correspondence matching method.

Delaunay Meshing and Model Construction We use the Delaunay triangulation to generate an adaptive triangle mesh with a set of points that are randomly distributed on face images. We design a simple meshing strategy: (1) select points that defines the boundary of the region to be modeled; (2) link those boundary points to form a polygon; (3) select the points that are inside the polygon; (4) generate a triangle mesh that is adaptive to all the selected points.

To ensure the mesh quality, we also design a local mesh refinement procedure that detects bad-shaped elements and improves the initial mesh accordingly: (1) node will be added at the region of high curvature to increase the accuracy of surface representation; (2) new node will subdivide the long and thin element into more regular-shaped element.

Forward Modeling and Strain Computation The deformation of a solid can be described by a motion equation that is derived from the conservation of momentum:

$$\nabla \cdot \sigma + \rho \mathbf{f_b} = \rho \frac{\partial^2 \mathbf{u}}{\partial t^2}, \tag{2}$$

where σ is stress tensor, $\mathbf{u}$ is displacement vector, ρ is mass density, $\mathbf{f_b}$ is body force and $\nabla\cdot$ is divergence operator.

We model face deformation with a linear elastic model using the generalized Hooke's law and Cauchy strain tensor:

$$\sigma = \mathbf{Ce}, \tag{3}$$

$$\varepsilon = \frac{1}{2}[\nabla \mathbf{u} + (\nabla \mathbf{u})^T], \tag{4}$$

where $\mathbf{e}$ is strain tensor, $\mathbf{C}$ is elastic coefficient tensor and ∇ is gradient operator with respect to displacement vector.

Combining the above equations with inhomogeneous and isotropic Young's modulus E and Poisson's ratio ν, we obtain the governing equation used in face model:

$$\nabla \cdot [\lambda(\nabla \cdot \mathbf{u})\mathbf{I} + G\nabla \mathbf{u} + G(\nabla \mathbf{u})^T] + \rho \mathbf{f_b} = \rho \frac{\partial^2 \mathbf{u}}{\partial t^2}, \tag{5}$$

where G and λ are the Lamé constants.

Equation (5) is solved numerically after being discretized over the Delaunay triangle mesh using the finite element method in variational formulation [15]. Since we are interested in static deformation only, the final forward model in the discrete matrix form becomes:

$$\mathbf{Ku} = \mathbf{F} \tag{6}$$

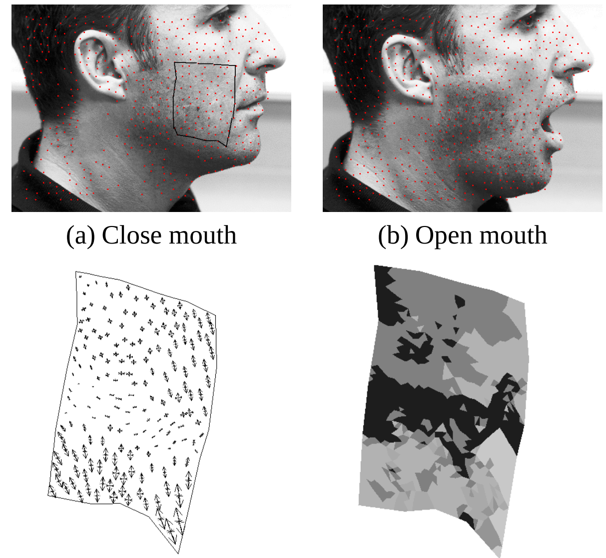
where $\mathbf{K}$ is stiffness matrix and $\mathbf{F}$ is the generalized force.

To compute the strain pattern of deformed face, we have to supplement appropriate boundary condition. We specify the Dirichlet condition using the measured displacement data on the feature points. As a result, it becomes an over-specified boundary value problem of the first kind and can be readily solved using an iterative numerical solver.

Strain Conversion and PCA Analysis We use the standard principle component analysis (PCA) [11] for performance assessment. To be compatible with commonly used face recognition methods that take the intensity images as inputs, we convert the strain maps into intensity images using a simple linear transformation:

$$\frac{e_x - e_{min}}{e_{max} - e_{min}} = \frac{I_x - I_{min}}{I_{max} - I_{min}} \tag{7}$$

where (e_{max}, e_{min}) are the maximum and minimum strain values for all subjects, e_x is the strain value to be converted, I_x is the converted intensity value. (I_{max}, I_{min}) are set to 255 and 0, respectively. Because strain value spans over a large range, information may be lost with this linear conversion. More sophisticated conversion method will be considered in future investigations.



(a) Close mouth (b) Open mouth

(a) Original strain map (b) Converted strain intensity

Figure 2. Strain pattern of a modified face that is attached with a less stretchable tape, which corresponds to small strain (low intensity).

Before PCA analysis, all converted strain intensity images are scaled based on the geometry of facial landmarks (nose, ear, mouth and jaw line). A rectangle region of the size of 150 by 160 pixels (original face images are 640 by 480 pixels) in the center of strain intensity image is then chopped out. This rectangle strain image will be used in PCA analysis. (See an example strain pattern in Figure 2).

4 Experimental Results

Data Set Two side-view images were acquired for each subject (open-mouth, close-mouth). Range images were also taken with a Minolta Vivid-900 range scanner to provide 3D data. Two more images were acquired for each subject under a different illumination condition. As a result, each subject has 4 images: open-mouth + bright-light, close-mouth + bright-light, open-mouth + dark-light, close-mouth + dark-light. The complete data set contains 56 subjects (224 images), from which we selected 27 subjects for the experiments. To study the efficacy of the proposed method in the presence of modified faces (tissue properties are changed due to surgery, trauma or burn, either intentionally or accidentally), a transparent rectangular tape was attached on the face of 7 subjects. The tape is less stretchable and thus has the same effect of modified faces and results in abnormal strain patterns. We performed 4 tests with different gallery sizes (Table 1). The results are presented with the standard cumulative match characteristic (CMC) curves.

Results with Regular and Modified Faces The purpose of Test-1 is to investigate whether elastic strain pattern has enough

Table 1. Data Set

	Gallery	Probe
Test-1	12 subjects of regular faces	27 mixed subjects
Test-2	7 subjects of modified faces	27 mixed subjects
Test-3	15 subjects with bright light	27 mixed subjects
Test-4	15 subjects with darker light	27 mixed subjects

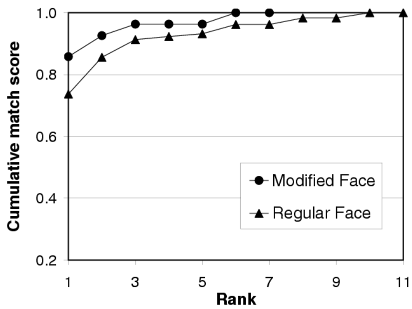


Figure 3. CMCs for regular and modified faces.

discrimination power for recognition of regular faces. Test-2 is to understand whether the modified faces are more difficult to recognize or more distinguishable due to an unusual strain pattern.

CMC curves of two tests are shown in Figure 3. The rank-one recognition score for regular faces is 73.7%. Although the results were obtained with a relatively small data set, the performance is still quite promising. The data set does not contain frontal views that are commonly used in face recognition test.

As expected, the experiment using modified faces shows a better performance with the rank-one score of 85.8%. This result suggests that a person who changed his/her appearance by plastic surgery or other approaches actually has a better chance to be detected because medical surgery cause property changes of facial tissues, which is hard to detect using the methods that rely on visible cues only.

Results with Illumination Changes Strain tensor can be roughly viewed as the derivative of displacement vector. Face recognition using strain pattern may be less sensitive to the illumination change, as long as it does not affect the image quality, and hence displacement quality, to a degree that the information contained in strain pattern is no longer good enough for recognition. To verify this, we carried out two tests. Test-3 has a gallery of 15 subject whose images were taken under brighter condition, while the gallery of Test-4 has 15 subjects whose image were taken with a darker light. Each gallery contains 5 subjects of modified faces (randomly picked) and 10 subjects of regular faces (randomly picked).

Figure 4 shows the CMC curves. At least for this experiment setting, no significant difference is observed. Since we have not yet experimented with larger illumination variations, the question whether illumination is a strong factor in a fully automated approach still remains unanswered.

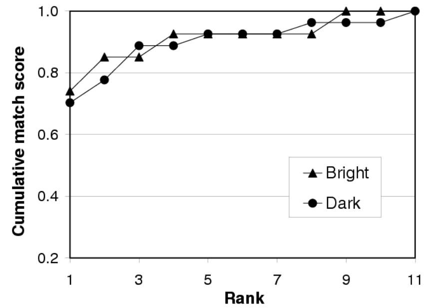


Figure 4. CMCs with illumination changes.

5 Conclusions

We present a face recognition method that utilizes the elastic strain pattern computed from the observed face motion. The rational for the new biometrics is that the underlying anatomical structure is unique for each individual and this physiological invariant can be explored for face recognition. The proposed method has the advantage that recognition reaches beyond the visible faces that are usually seen and used by other face recognition methods, which can be confused by various camouflage using plastic surgery or makeup.

Several issues that need to be addressed in future investigations are: (1) a larger data set is needed to thoroughly evaluate the performance; (2) correspondence matching needs to be automated. Optical flow and motion measurement in video sequence also can be considered; (4) using strain pattern on the whole face rather than a portion of face; (5) a comparative study with other methods is necessary. Fully aware of its limitation, we do not foresee that the method can solve the face recognition problem. Instead, we envision that it has a great chance to enhance the existing methods when used collaboratively, because it targets completely different facial attributes than current face biometrics.

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