Facial strain maps as a biometric source

Sangeeta J. Kundu
University of South Florida
Facial Strain Maps As A Biometric Source

by

Sangeeta J. Kundu

A thesis submitted in partial fulfillment of the requirements for the degree of Master of Science in Computer Science
Department of Computer Science and Engineering
College of Engineering
University of South Florida

Co-Major Professor: Dmitry B. Goldgof Ph.D.
Co-Major Professor: Sudeep Sarkar, Ph.D.
Rangachar Kasturi, Ph.D.

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DEDICATION

To Ma, Baba and my loving brother Sudeep.
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# TABLE OF CONTENTS

LIST OF TABLES iii

LIST OF FIGURES iv

ABSTRACT vii

CHAPTER 1 INTRODUCTION 1
   1.1 Overview 1
   1.2 Literature Review: Previous Work 3
      1.2.1 Current Face Recognition Techniques 3
         1.2.1.1 Static Face Recognition 3
         1.2.1.2 Video-Based Face Recognition 5
      1.2.2 Importance of Facial Motion for Face Recognition 6
         1.2.2.1 Object Reconstruction 7
         1.2.2.2 Nonrigid Motion Analysis 8
         1.2.2.3 Elastic Motion 9
         1.2.2.4 Material Property Reconstruction 9
      1.2.3 Summary: Proposed Solution 10

CHAPTER 2 FACE MODEL 11
   2.1 Theory of Elasticity 11
      2.1.1 Stress And Strain Analysis 11
      2.1.2 Material Behavior 14
         2.1.2.1 Static Equilibrium of Elastic Bodies in Terms of Displacements 15
      2.1.3 Deformation Equation For Linear Elastic Object 16
   2.2 Physics Based Modelling 17

CHAPTER 3 STRAIN COMPUTATION 18
   3.1 Data Collection 18
   3.2 Computational Method
      3.2.1 Theory Of Strain Using 2D Displacements 20
      3.2.2 Algorithm
         3.2.2.1 Feature Extraction 24
         3.2.2.2 Feature Correspondence 26
         3.2.2.3 Pixel Interpolation of Displacements 27
         3.2.2.4 Calculate Strain $(S_x, S_y)$ from $(U_x, U_y)$ 27
         3.2.2.5 Normalize Strain Values 31
CHAPTER 4  FACE RECOGNITION AND IDENTIFICATION  37
 4.1  Principal Components Analysis (PCA)  37
    4.1.1  PCA Algorithms  37
      4.1.1.1  Preprocessing  38
      4.1.1.2  Training  40
      4.1.1.3  Testing  40
      4.1.1.4  Analysis  40
 4.2  Experiments and Results  43
    4.2.1  Experiment 1  44
    4.2.2  Experiment 2  45
      4.2.2.1  Averaging ROC Curves  46
    4.2.3  Experiment 3  48
      4.2.3.1  Analysis  48
    4.2.4  Experiment 4  53
      4.2.4.1  Analysis  55
    4.2.5  Experiment 5  57

CHAPTER 5  CONCLUSION AND FUTURE WORK  58
 5.1  Conclusion  58
 5.2  Future Work  59

REFERENCES  60
LIST OF TABLES

Table 1.1  Typical Applications Of Face Recognition  2
Table 1.2  Object’s Attributes And The Reconstruction Methods  7
Table 4.1  Experiments  43
Table 4.2  Top Ten Ranks Of Identification For Normal Intensity Faces, Strain Of Normal Faces, And Of (Strain+Normal) Faces  51
Table 4.3  Top Ten Ranks Of Identification For Different Expression Intensity Normal Faces, Strain Of Normal Faces Under Different Illumination, And Of (Strain+Intensity) Faces  56
# LIST OF FIGURES

<p>| Figure 3.1 | Profile Face Images Of A Subject Under Different Lighting Conditions | 19 |
| Figure 3.2 | Undeformed And Deformed Geometry Of A Solid | 20 |
| Figure 3.3 | From Displacements To Strain Map | 22 |
| Figure 3.4 | Strain As A Function Of Displacements | 24 |
| Figure 3.5 | Strain Computation Using Derivative Of Motion Field | 25 |
| Figure 3.6 | GroundTruth To Understand The Displacement Field | 28 |
| Figure 3.7 | Facial Motion And Displacement Vectors | 29 |
| Figure 3.8 | Pixel Interpolation of Displacements | 30 |
| Figure 3.9 | Displacements Ux, Uy Converted to Intensity After Interpolation | 30 |
| Figure 3.10 | Strain Maps Of Normal Faces Under Different Lighting Conditions | 32 |
| Figure 3.11 | Strain Map Of A Normal Face | 33 |
| Figure 3.12 | Strain Map Of A Modified Face | 33 |
| Figure 3.13 | Strain Maps Of Normal Faces | 34 |
| Figure 3.14 | Strain Maps Of Modified Faces | 35 |
| Figure 3.15 | Mean Strain Map Of Normal Faces | 36 |
| Figure 3.16 | Mean Strain Map Of Modified Faces | 36 |
| Figure 4.1 | Geometric Normalization And Masking For PCA | 39 |
| Figure 4.2 | Match Example | 42 |
| Figure 4.3 | Non Match Example | 42 |
| Figure 4.4 | CMC-Profile Images Of 50 Subjects Showing The Identification Rate Of Illumination Variation For Closed Mouth | 44 |
| Figure 4.5 | ROC-Profile Images Of 50 Subjects Showing The Identification Rate Of Illumination Variation For Closed Mouth | 44 |</p>
<table>
<thead>
<tr>
<th>Figure</th>
<th>Description</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>4.6</td>
<td>CMC-StrainMaps Of 50 Regular Subjects Showing The Performance Of The StrainMap Biometric Under Different Illumination Conditions</td>
<td>45</td>
</tr>
<tr>
<td>4.7</td>
<td>ROC-StrainMaps Of 50 Regular Subjects Showing The Performance Of The StrainMap Biometric Under Different Illumination Conditions</td>
<td>45</td>
</tr>
<tr>
<td>4.8</td>
<td>ROC Curves For The Strainmap Biometric From 50 Test Samples</td>
<td>46</td>
</tr>
<tr>
<td>4.9</td>
<td>ROC Curve From Combining The 50 Test Samples</td>
<td>47</td>
</tr>
<tr>
<td>4.10</td>
<td>ROC Curve Obtained By Vertical Averaging The True Positives At A Sampled False Positive</td>
<td>47</td>
</tr>
<tr>
<td>4.11</td>
<td>MultiClassifier: Profile Plus Strain Map</td>
<td>48</td>
</tr>
<tr>
<td>4.12</td>
<td>CMC-StrainMaps Of 50 Regular Subjects Showing The Performance Of The Multi Classifier - Strain Plus Intensity</td>
<td>49</td>
</tr>
<tr>
<td>4.13</td>
<td>ROC-StrainMaps Of 50 Regular Subjects Showing The Performance Of The Multi Classifier - Strain Plus Intensity</td>
<td>49</td>
</tr>
<tr>
<td>4.14</td>
<td>CMC-Identification Performance Of Face, Strain Map, And Face+Strain Map Concatenated Biometrics</td>
<td>50</td>
</tr>
<tr>
<td>4.15</td>
<td>Distribution Of The Match And No-Match Class. a.Intensity Normal Faces b.Strain Normal Faces c.Strain+Intensity Normal Faces</td>
<td>52</td>
</tr>
<tr>
<td>4.16</td>
<td>CMC-Profile Images Of 50 Subjects Showing The Identification Rate For Expression Change(Closed Mouth v/s Open Mouth)</td>
<td>53</td>
</tr>
<tr>
<td>4.17</td>
<td>ROC-Profile Images Of 50 Subjects Showing The Identification Rate For Expression Change(Closed Mouth v/s Open Mouth)</td>
<td>53</td>
</tr>
<tr>
<td>4.18</td>
<td>CMC-Combined Biometric Of Strain And Intensity For 50 Subjects For Different Expression And Different Illumination Condition</td>
<td>54</td>
</tr>
<tr>
<td>4.19</td>
<td>ROC-Combined Biometric Of Strain And Intensity For 50 Subjects For Different Expression And Different Illumination Condition</td>
<td>54</td>
</tr>
<tr>
<td>4.20</td>
<td>CMC-Identification Performance Of Intensity Different Expression, Strain Map Different Illumination, And Face+Strain Map Concatenated Biometrics</td>
<td>55</td>
</tr>
<tr>
<td>4.21</td>
<td>Distribution Of The Match And No-Match Class. a.Intensity Normal Faces Different Expression c.Strain+Intensity Normal Faces Different Expression Different Illumination</td>
<td>56</td>
</tr>
<tr>
<td>4.22</td>
<td>CMC-StrainMaps Of 12 Modified Subjects Showing The Performance Of The StrainMap Biometric Under Different Illumination Conditions</td>
<td>57</td>
</tr>
</tbody>
</table>
Figure 4.23  ROC-StrainMaps Of 12 Modified Subjects Showing The Performance Of The StrainMap Biometric Under Different Illumination Conditions
FACIAL STRAIN MAPS AS A BIOMETRIC SOURCE

Sangeeta J. Kundu

ABSTRACT

Current two dimensional face recognition methods rely on visible photometric or geometric attributes that are present in the intensity image. In many of these approaches a technique called Principal Component Analysis (PCA) is extensively used. PCA extracts the maximum intensity variations from the set of input images in the form of “eigen” faces which are used as a feature vector. In these approaches the intensity images used were mostly that of the subject’s frontal face, which yielded promising results after doing PCA. These approaches however fail in the presence of facial expression, unstable lighting conditions and artifacts such as make-up, glasses etc. Thus, it is desirable to establish a new biometric source that will be least affected by the aforementioned factors. This study describes a face recognition method that is designed based on the consideration of anatomical and biomechanical characteristics of facial tissues.

During facial expressions such as smile, frown, anger etc, various muscles get activated in tandem. A strain pattern inferred from a face expression can reveal an individual’s signature associated with the underlying anatomical structure, and thus has the potential for face recognition. In this study, the strain is computed by measuring the displacement of a point on the face that results from a facial expression such as opening the mouth.

The information provided by the change in the depth value for the face across the open and close mouth frames does not provide any information required for computing the strain maps, because the strain map depends on the relative displacements of two points on the face, which remains same with rigid motions of the face such as rotation and translation. Hence the information in the 2D space is sufficient to compute strain since the depth is
assumed constant. The approach used to calculate strain computes the strain distribution directly using the mathematical definition of strain as the derivative of displacement in 2D space (XY plane). The strain values obtained are converted to gray scale intensity images, which are used as inputs for the intensity based PCA analysis.

Experiments were conducted using 62 subjects. The data set comprised of two pairs of images for a subject: closed mouth and open mouth under bright and low light. Analysis of CMC and ROC curves indicate that the proposed strain map biometric is a promising new biometric that has the potential to improve the performance of current face recognition method.

In summary, the contribution of this thesis is twofold:

1. Facial strain map proves to be promising new biometric.

2. Strain map helps increase the identification rate when used in conjunction with intensity based biometric as a multi-classifier.
CHAPTER 1
INTRODUCTION

1.1 Overview

In day to day life, one encounters numerous authentication and identification systems, for example a pin to an ATM machine or a password to access one’s account. These authentication metrics no doubt have proven to be robust, but they come at the cost of the individual’s cooperation, need to be carried around, and may not necessarily prove to be unique enough to identify an individual.

In the past decade, focus has shifted to systems which deal with some distinctive physical characteristics/personal traits of individuals which is known as biometrics. Biometrics is any automatically measurable, robust and distinctive characteristic that can be used to identify an individual or verify the claimed identity of an individual [50]. Any metric that can be easily made available to the sensors, is less variant with time or other external factors, and lastly captures the distinct variations in the biometric pattern amongst the general population qualifies to be a perfect biometric source[50].

This type of biometric reduces the risk of unauthorized users along with the inconvenience of carrying it since it is a part and parcel of the individual. During the past couple of years with the rise in terrorism, especially after the attack of 9/11, biometrics [12] research has received considerable attention: first due to its high potential in security related applications and the second due to the availability of feasible technologies in image analysis and understanding.

Examples of some of the popular biometric sources are: Iris scan, Retinal scan, Facial recognition, Speaker or Voice, Fingerprint, Hand or Finger geometry, Signature verification, Keystroke dynamics, Human Gait, Ear etc[50].
Of the few biometric techniques listed above, some are relatively mature while some 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. Although biometrics such as finger prints, iris and retinal scans are reliable identification techniques, they rely on the cooperation and assistance of the individuals. Comparatively, identification systems based on profile or frontal images of the face of an individual is found to be effective even without the participation [57] of the individual which thus makes it a natural and popular biometric. Face recognition finds a place in many specific applications which either involve security issues, surveillance, entertainment etc. Table 1.1 lists some of the applications of face recognition[57].

<table>
<thead>
<tr>
<th>Areas</th>
<th>Specific applications</th>
</tr>
</thead>
<tbody>
<tr>
<td>Entertainment</td>
<td>Video game, virtual reality, training programs, Human-robot-interaction, human-computer-interaction</td>
</tr>
<tr>
<td>Smart cards</td>
<td>Drivers' licenses, entitlement programs, Immigration, national ID, passports, voter registration, Welfare fraud</td>
</tr>
<tr>
<td>Information security</td>
<td>TV Parental control, personal device logon, desktop logon, Application security, database security, file encryption, Intranet security, internet access, medical records, Secure trading terminals</td>
</tr>
<tr>
<td>Law enforcement and surveillance</td>
<td>Advanced video surveillance, CCTV control, Portal control, post event analysis, Shoplifting, suspect tracking and investigation</td>
</tr>
</tbody>
</table>

How does a human recognize a person from another, and what is the information that he stores for the unique identity associated with the person is like a black box. Human recognition processes utilize a broad spectrum of stimuli, obtained from various senses such as visual, auditory, tactile, etc., but it is difficult to state which sense/senses are actually responsible for the process [57]. Face perception is an important part of the capability to recognize a human, which is a routine task for individuals but it is very difficult to mimic the exact human recognition ability on a machine. But we do need machines/computers to
recognize faces to automate the process and secondly the biggest advantage of a computer system is its capacity to handle large numbers of face images.

1.2 Literature Review: Previous Work

1.2.1 Current Face Recognition Techniques

Face perception and recognition is a routine task for humans, while building an equally effective and efficient computer system is still an on-going research area. The earliest work on face recognition is in psychology by Bruner[11] and Bledsoe[7] in 1964 followed by the research on automatic machine recognition of faces in the 1970s [56]. Over the last 30 years, the complexity in designing a robust computer system for face recognition has attracted psychologists, neuroscientists and engineers to study the various aspects of face recognition by humans and machines. Consequently, this has lead to the investigation of myriads of diverse techniques to study different stages of face recognition individually as well as the complete process as a whole. These techniques, however, can be classified into two groups depending on whether they make use of static images or a sequence of images containing a facial pattern typically obtained from a video [56]. Each of these methods has pros and cons in terms of how they tackle the common problems such as image quality, background complexity, pose variations of the individual to be recognized, and the nature of the user input.

1.2.1.1 Static Face Recognition

Face recognition based on static images can be viewed as 2D matching and recognition of the 3D face object. Since 2D color or intensity images are easily obtained in real-time, most of the work on face recognition has been focused on these images. However, other forms of image modalities such as range images [19, 10, 6, 5], sketches [9, 13] and thermal images [45] have also been used. The process of face recognition involves detection, feature extraction followed by the identification and/or verification. Lot of research has been done on the individual steps of the recognition pipeline because without an accurate localization
of face and features a considerable degradation in the recognition performance has been observed [31, 55]. The face detection has been carried out by various methods such as feature based template-matching [23] and appearance or image based methods [40, 46] that train the machine systems on large number of samples. The later has achieved the best results. Most recently face detection under rotation in depth has been studied [21, 41] which has led to an important conclusion that for small angles, face perception is viewpoint-independent, while for large angles it is view-dependent [56]. The feature extraction is usually done simultaneously with the detection. Earlier methods on feature extraction used templates to detect facial features such as eyes and mouth in the real images [52]. They modeled the feature extraction as a minimization of energy function that linked the edges, peaks and valleys in the image intensity to the corresponding properties in the template. These models are surpassed by more robust and flexible statistical appearance models such as Active Shape Model (ASM) proposed in [14] and its more recent advancement called Flexible Appearance Model (FAM) [15]. The recognition methods over the last 30 years have mainly focused on using the whole face (holistic), features extracted from the faces (feature-based or structural) or a combination of both (hybrid) as an input to the classifier [56]. The holistic methods mainly use Principal component analysis (PCA) [49] to generate eigen faces from the set of training images and projects them into the eigen space. Many techniques have used PCA as base technique. These include: eigen face methods which use nearest neighbor classifier [16]. Higher order statistical analysis techniques such as Independent Component Analysis (ICA) are found to be better than PCA by [4]. The most successful methods in the structural methods category is the graph matching system [34]. The hybrid methods include modular eigenface method [37], combination of PCA and local feature analysis(LFA) and a recent development using hybrid approach was done by[24] along this direction. Though the still image based techniques have achieved considerable success they are still far from the human recognition systems. They are typically posed with problems such as sensitivity to the geometric change and accurate feature locations.
1.2.1.2 Video-Based Face Recognition

Recent studies in psychology and neural studies indicate that the facial movements can alleviate some of the problems faced in the still image based recognition [35]. Inspired by these findings, researchers are exploiting the potential of face dynamics, determined from the temporal information contained in the video sequences, for face recognition. Automatic face recognition from video finds applications in information security, access control and video surveillance. The algorithms in this case, however, are faced with new challenges such as poor image quality, small image sizes which are generally not present in case of still images. The key to building a successful video-based system is to use temporal information to compensate for the lost spatial information due to poor image quality. A typical video-based face recognition system automatically detects face regions, extracts features from the video, and recognizes facial identity if a face is present. They typically involve tracking the face (head tracking) and facial features (tracking nonrigid deformations) to extract the depth information, which in turn can be used to create 3D models of the face. There are two sub classes in the video based face recognition depending on how they use the temporal information in the image sequence [56]. The first category includes methods that apply the still image based algorithms on selected frames and hence do not fully use the information contained in the image sequences for facial dynamics. Methods proposed by [20] fall into the first category. It tracks the positions of nose and eyes and if they form an equilateral triangle an image-based recognition is launched; otherwise the tracking continues until a "good" frame occurs. The other methods that use the abundance of the frames in a video are the probabilistic voting schemes [18]. The second category of video based algorithms, exploit the temporal information more efficiently by incorporating spatio-temporal representations of the face. Some of the approaches using this principle include the condensation method [59] and the method based on HMM [58]. Other methods include Auto-regressive and moving average (ARMA) model, and recognition using probabilistic appearance [30]. The comparison of the two approaches is presented in [22].
With the plethora of techniques and theories proposed for the face recognition it becomes necessary to evaluate their performances on the common grounds. Several attempts have been made in the last 5 years to provide large databases of faces available to the research community. Corresponding test protocols are also in place to evaluate the performance of an algorithm. One of the most popular databases is FERET [38], which contains 14, 126 images (1199 original sets and 365 duplicate sets).

Despite the different techniques ranging from static to dynamic building an accurate face recognition system which mimics the human recognition capability is still a challenge and is hindered by problems such as intensity and pose variation. Hence the need for different techniques still exists.

Future face recognition methods must address these difficult issues. We propose a new class of features (or biometrics) that is derived from the computed strain pattern exhibited during facial expression. The proposed method has several advantages and is based on the following factors:

1. Unique anatomical structure resulting in unique facial strain pattern.

2. Strain is directly related to facial expression.


1.2.2 Importance of Facial Motion for Face Recognition

Until recently, most research on face recognition was carried out using static images, such as intensity based images. The shortcomings of these methods in addition to the fact that faces are in constant motion in the real world such as talk, laugh, nod, etc. led to the exploration of the role of movement in the recognition of faces. It has been shown that, in addition to facilitating communication, such motion can also convey information about emotion, age, gender and to some extent about identity [42]. The questions that arise are: How exactly does motion help identify a face and what type of motion comprises the facial motion? Facial movements could involve either nonrigid transformations such as changes in expression (ex. smile) or rigid motion such as rotation of head (ex. nodding or
shaking). A recent study showed that famous faces are easier to recognize when shown in moving sequences than in still photographs [28]. The study shows that even under difficult conditions wherein the images were negated, inverted or thresholded, facial movement played a significant role in the recognition of familiar faces [57]. To understand facial motion we need to first look into object reconstruction from 2D image sequences, nonrigid motion aspects involved in the movement of face and facial expressions, and the various motion estimation models, which aid in the recognition and identification.

1.2.2.1 Object Reconstruction

Object reconstruction is an important step towards performing object recognition and pattern analysis in computer vision. The attributes which contribute to an objects composition, makes it different from other objects differing in the composition or accommodates it in a group of objects having similar attribute values. For example in case of face recognition each face has certain geometric attributes, such as position, shape; surface attributes - such as color, texture; or material attributes, such as elasticity of skin; etc. [53]. Some of the most used attributes and their related reconstruction methods are listed in Table 1.2 [53].

<table>
<thead>
<tr>
<th>Attribute Types</th>
<th>Examples</th>
<th>Methods and Terminologies</th>
</tr>
</thead>
<tbody>
<tr>
<td>geometric</td>
<td>position, shape</td>
<td>structure reconstruction</td>
</tr>
<tr>
<td>surface</td>
<td>color, texture</td>
<td>surface reconstruction</td>
</tr>
<tr>
<td>kinematic</td>
<td>deformation matrix</td>
<td>motion analysis</td>
</tr>
<tr>
<td>dynamic</td>
<td>force, boundary conditions</td>
<td>motion analysis</td>
</tr>
<tr>
<td>material property</td>
<td>elasticity, conductivity</td>
<td>material property estimation</td>
</tr>
</tbody>
</table>

These attributes act as an abstraction to the real object and they are used to model the real object in a mathematical language. Depending on the varying level of accuracy required and the complexity involved in building the model, several of the above attributes can be utilized. All the real world objects that can be characterized and modelled using the same set of attributes can be classified into a class [3]. A model can then be constructed
to represent the set of attributes forming the class. In this study we have used the kinematic (motion analysis - discussed in the next section) and material property (elasticity) attributes to model the human face. The nonrigid motion is estimated between two facial expressions of an individual which is used to reconstruct the material properties of the facial skin in terms of strain exerted in undergoing the change in expression.

1.2.2.2 Nonrigid Motion Analysis

In the real world, the motion of physical objects is generally nonrigid. Therefore there is a growing interest in the study of nonrigid motion which helps in applications such as surveillance, gesture recognition, face recognition, medical diagnosis, image compression, graphics animation etc. [2]. In addition it also finds applications in measurement of an object's material property through image processing, particularly in biomedical research such as burn scar assessment, cardiac diagnosis and cancer detection [48, 8, 33, 53]. Likewise in computer vision, motion information from 2D image sequences has been used for dealing with the highly nonlinear problem of reconstructing a 3D object that undergoes a complex motion pattern across images.

Nonrigid motion was first classified into three categories: articulated motion, elastic motion, and fluid motion - by Huang [25]. Kambhamettu et al [27] further classified the nonrigid motion based on the degree of nonrigidity of the objects: articulated motion, quasi-rigid motion, isometric motion, homothetic motion, conformal motion, elastic and fluid motion [2]. Aggarwal et al [2] went a step ahead and summarized nonrigid motion based on whether a shape model is used: model-based and non-model based. The model-based approaches are further broken down to those using parametric shape model and those using physically based models [2]. In other words, motion model (motion equations) describe the motion attributes of an object, while shape model (structure) describe the geometrical attributes of the object [2, 53]. The motion of an object can be studied by analyzing the motion trajectory of the points on an object through a series of deformation matrices, or by analyzing the forces that cause the motion [53, 2]. The model-based approach is motivated from the fact to deal with objects which are more complex in nature. In this
study a model-based approach to recover the rigid and non-rigid facial motion parameters in 2D images displaying motion is presented.

1.2.2.3 Elastic Motion

To understand facial motion, we first need to classify this motion in one of the above categories and then further decide on the best approach for estimating the motion involved. The face movement can be very closely related to elastic motion since elastic motion refers to the type of nonrigid motion whose only constraint is some degree of continuity or smoothness [2]. And secondly human skin being elastic in nature (regains original shape and form once the applied forces under which the deformation occurs, are removed), facial motion is categorized under elastic motion. Most approaches that deal with elastic motion assume an object model and then try to model the deformations as variations to the model parameters [1].

1.2.2.4 Material Property Reconstruction

The need for biomechanical modeling in medical research and diagnosis, and for accurate deformation prediction, material property estimation is the need of the hour in computer vision and medical imaging fields and helps in more accurate 3D object reconstruction [3]. Tsap et al.[48] presented an approach for quantitative evaluation of burn scars based on the abnormal skin elasticity measured from motion estimation across several frames. Accurate data about the derived material properties can help detect irregular tissues in various human organs (for example, the face with a scar will exhibit elasticity different from that exhibited by normal skin).

Material property in general cannot be measured directly in addition to the fact that we are trying to estimate it from static images. Hence it must be estimated using variables that can be obtained from images, such as displacements and velocity fields, and which relate to the underlying material properties closely to minimize the difference between model predictions and the actual observations.
1.2.3 Summary: Proposed Solution

The use of the strain maps as a biometric source for face recognition is proposed and investigated. The hypothesis is that, the strain pattern captures the uniqueness of an individual because it is related to the material property of underlying facial muscles and hence can be exploited for face 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, injuries and plastic surgery.

The computation of elastic strain map requires at least two frames that capture the face deformation during expression. The strain is traditionally computed as derivatives of the motion field along the $x$, $y$ directions. Only a section of the face between the cheek bone and jaw line (side view) is chosen to measure the deformations caused by opening the mouth.

Even though the use of anatomy-based physical models is widely used in realistic facial animation and surgery simulation [36, 47, 29] and to represent facial motion and distinguish face expressions [43], its use for face recognition still remains unexplored. In the face recognition literature on static images the performance of the algorithms is shown to have adverse effects with the dynamic expressions [51]. These methods have predominantly used visible cues for the recognition. We want to go one step further beyond the visible cues in face expression to recover the elastic strain pattern that might help reveal the underlying anatomical individuality.
CHAPTER 2

FACE MODEL

2.1 Theory of Elasticity

2.1.1 Stress And Strain Analysis

When external forces are exerted on a body, the forces acting on it could be surface forces (such as fluid pressure) which act over the surface of the solid, or it could be body forces, which are distributed over the volume of the solid. The transmission of these forces through a solid entails the generation of internal forces. To study these forces, we use a continuum model of the material in which matter is assumed to be continuously distributed throughout the solid [17].

When a solid body is under equilibrium under the action of external forces, to measure the intensity of each of these forces we define the quantity stress. Stress is used to measure the state of the force acting on the solid, or in simple words, it means the force acting per unit area. Stresses are decomposed into three components [17] based on the different forces acting on the plane of the solid as follows:

\[
\sigma_{xx} = \lim_{\Delta A \to 0} \left( \frac{\Delta F_x}{\Delta A} \right) \quad (2.1)
\]

\[
\tau_{xy} = \lim_{\Delta A \to 0} \left( \frac{\Delta F_y}{\Delta A} \right) \quad (2.2)
\]

\[
\tau_{xz} = \lim_{\Delta A \to 0} \left( \frac{\Delta F_z}{\Delta A} \right) \quad (2.3)
\]
The component \( (\sigma_{xx}) \) is the normal stress which measures the intensity of the normal force on the plane at the point. The components \( (\tau_{xy}) \) and \( (\tau_{xz}) \) are the shear stresses which measure the intensity of the shear force on the plane. Normal stresses tend to change the volume of the material whereas shear stress tend to deform the material without changing the its volume. It can be shown that only the normal and shear stresses on any three orthogonal planes are sufficient to describe the complete state of stress at a point. The stress tensor comprising the stress components [32, 17] can be organized in the matrix form as follows:

\[
[\sigma] = \begin{bmatrix}
\sigma_{xx} & \tau_{xy} & \tau_{xz} \\
\tau_{yx} & \sigma_{yy} & \tau_{yz} \\
\tau_{xx} & \tau_{zy} & \sigma_{zz}
\end{bmatrix}
\] (2.4)

There are six distinct stress components, along with three complementary shear stresses across the diagonal which are identical, i.e. \( (\tau_{xy} = \tau_{yx}), (\tau_{yz} = \tau_{yz}), (\tau_{xx} = \tau_{xx}) \).

When external forces act on a body, there is another measure which has to considered to measure the deformation the body undergoes which is known as strain. It is shown that under forces, the changes in the body’s configuration(geometry) can be defined in terms of the displacements of each point in the body. There are two types of displacements possible: one is rigid-body displacements and the second is deformation. Rigid body displacements consists of translations and rotations of the body as a whole, whereas deformation consists of displacements of points within the body relative to one another [17]. Strain is used to quantify the deformation undergone. The direct strain \( (\varepsilon) \) is defined as:

\[
\varepsilon = \frac{ds' - ds}{ds}
\] (2.5)

where \( (ds) \) is the original length and \( (ds') \) is the deformed length.

An infinitesimal strain tensor is defined as:

\[
[e] = \frac{1}{2}[\nabla u + (\nabla u)^T]
\] (2.6)
where $\mathbf{u}$ is a displacement vector.

In 3D coordinate system, the displacement vector $\mathbf{u}$ has three components $u, v, w$, in the $x, y, z$ directions which gives rise to six strain measures (three normal strains and three shear strains) [17] as shown below:

$$
\varepsilon_{xx} = \frac{\partial u}{\partial x}, \quad \varepsilon_{yy} = \frac{\partial v}{\partial y}, \quad \varepsilon_{zz} = \frac{\partial w}{\partial z} \tag{2.7}
$$

$$
\tau_{xy} = \frac{\partial u}{\partial y} + \frac{\partial v}{\partial x}, \quad \tau_{yz} = \frac{\partial v}{\partial z} + \frac{\partial w}{\partial y}, \quad \tau_{zx} = \frac{\partial w}{\partial x} + \frac{\partial u}{\partial z} \tag{2.8}
$$

The state of strain in 3D is then defined by:

$$
[\sigma] = \begin{bmatrix}
\varepsilon_{xx} & \frac{1}{2}\gamma_{xy} & \frac{1}{2}\gamma_{xz} \\
\frac{1}{2}\gamma_{yx} & \varepsilon_{yy} & \frac{1}{2}\gamma_{yz} \\
\frac{1}{2}\gamma_{zx} & \frac{1}{2}\gamma_{zy} & \varepsilon_{zz}
\end{bmatrix} \tag{2.9}
$$

The strain-displacement Equations 2.7, 2.8 are the six strain components in terms of displacements $u, v, w$. In the 3D strain tensor matrix, there are six independent values but there are only three displacements, we need another set of three equations to eliminate $u, v, w$ between the six equations. The next set of three differential equations not involving $u, v, w$ must be met to govern the state of strain within a solid [3, 17],

$$
\frac{\partial^2 \varepsilon_{xx}}{\partial y^2} + \frac{\partial^2 \varepsilon_{yy}}{\partial x^2} = \frac{\partial^2 \gamma_{xy}}{\partial x \partial y}, \quad 2\frac{\partial^2 \varepsilon_{xx}}{\partial y \partial z} = \frac{\partial}{\partial x} \left( -\frac{\partial \gamma_{yz}}{\partial x} + \frac{\partial \gamma_{yx}}{\partial y} + \frac{\partial \gamma_{xy}}{\partial z} \right) \tag{2.10}
$$

$$
\frac{\partial^2 \varepsilon_{yy}}{\partial z^2} + \frac{\partial^2 \varepsilon_{zz}}{\partial y^2} = \frac{\partial^2 \gamma_{yz}}{\partial y \partial z}, \quad 2\frac{\partial^2 \varepsilon_{yy}}{\partial z \partial x} = \frac{\partial}{\partial y} \left( \frac{\partial \gamma_{yx}}{\partial x} + \frac{\partial \gamma_{xy}}{\partial z} + \frac{\partial \gamma_{yz}}{\partial y} \right) \tag{2.11}
$$

$$
\frac{\partial^2 \varepsilon_{zz}}{\partial x^2} + \frac{\partial^2 \varepsilon_{xx}}{\partial z^2} = \frac{\partial^2 \gamma_{zx}}{\partial z \partial x}, \quad 2\frac{\partial^2 \varepsilon_{zz}}{\partial x \partial y} = \frac{\partial}{\partial z} \left( \frac{\partial \gamma_{zx}}{\partial x} + \frac{\partial \gamma_{xx}}{\partial y} - \frac{\partial \gamma_{xy}}{\partial z} \right) \tag{2.12}
$$
2.1.2 Material Behavior

In the previous section, we analyzed the stress and strain at a point in a solid. In this section we include the details of the material behavior to completely describe the behavior of the solid. To describe the stress-strain characteristics of an engineering material, we select a model which approximates the actual behavior [17]. Since in this study, we deal with the human skin which is elastic in nature, we concentrate on the elastic behavior of the object. (An elastic material is defined as one in which the object regains original shape and form when the forces are removed).

To completely describe the elastic nature of the object, many material constants are needed to relate the deformation and the forces causing the deformation. For linear, homogenous and isotropic (material property same in all directions) bodies such as human skin, the two important material parameters considered are Young’s modulus $E$ and Poisson’s ratio ($\nu$) defined as follows:

$$e_{xx} = \frac{\sigma_{xx}}{E} \quad (2.13)$$

And Poisson’s ratio is given by:

$$e_{yy} = e_{zz} = -\nu \frac{\sigma_{xx}}{E} \quad (2.14)$$

If the strain is a linear function of the components of stress such as:

$$e_{xx} = c11\sigma_{xx} + c12\sigma_{yy} + c13\sigma_{zz} + c14\gamma_{xy} + c15\gamma_{yx} + c16\gamma_{zz} \quad (2.15)$$
where the elastic coefficients c11, c12, c13, c14, c15, c16 are the same for every point, then
the material is said to be linearly elastic and can be described by Hook’s law as follows:

\[
\begin{bmatrix}
\sigma_{xx} \\
\sigma_{yy} \\
\sigma_{zz} \\
\tau_{xy} \\
\tau_{yz} \\
\tau_{zx}
\end{bmatrix} =
\begin{bmatrix}
c_{11} & c_{12} & c_{13} & c_{14} & c_{15} & c_{16} \\
c_{21} & c_{22} & c_{23} & c_{24} & c_{25} & c_{26} \\
c_{31} & c_{32} & c_{33} & c_{34} & c_{35} & c_{36} \\
c_{41} & c_{42} & c_{43} & c_{44} & c_{45} & c_{46} \\
c_{51} & c_{52} & c_{53} & c_{54} & c_{55} & c_{56} \\
c_{61} & c_{62} & c_{63} & c_{64} & c_{65} & c_{66}
\end{bmatrix}
\begin{bmatrix}
e_{xx} \\
e_{yy} \\
e_{zz} \\
\gamma_{xy} \\
\gamma_{yz} \\
\gamma_{zx}
\end{bmatrix}
\]  \(2.16\)

where \([\varepsilon]\) is the stress tensor, \([\sigma]\) is the strain tensor and \([\varepsilon]\) is elastic coefficient
tensor[17]. Thus Hook’s law can be put together as:

\[
\sigma = C \cdot \varepsilon
\]  \(2.17\)

2.1.2.1 Static Equilibrium of Elastic Bodies in Terms of Displacements

For static equilibrium conditions, the six stress components must satisfy the following
three equations of equilibrium.

\[
\frac{\partial \sigma_{xx}}{\partial x} + \frac{\partial \sigma_{yx}}{\partial y} + \frac{\partial \sigma_{zx}}{\partial z} + f_x = 0
\]  \(2.18\)

\[
\frac{\partial \sigma_{xy}}{\partial x} + \frac{\partial \sigma_{yy}}{\partial y} + \frac{\partial \sigma_{zy}}{\partial z} + f_y = 0
\]  \(2.19\)

\[
\frac{\partial \sigma_{xz}}{\partial x} + \frac{\partial \sigma_{yz}}{\partial y} + \frac{\partial \sigma_{zz}}{\partial z} + f_z = 0
\]  \(2.20\)

where \(f_x, f_y, f_z\) are the components of the resultant force \(f\) [17]. Similarly the six strain
components must comply with the following set of three compatibility equations. By expressing
the strains in terms of the displacements, using the strain-displacement equations 2.7 2.8,
we can then write the three equilibrium equations in terms of displacements as:
\( (\lambda + G) \frac{\partial \varepsilon}{\partial x} + G \nabla^2 u + b_x = 0 \) \hspace{1cm} (2.21)

\( (\lambda + G) \frac{\partial \varepsilon}{\partial y} + G \nabla^2 v + b_y = 0 \) \hspace{1cm} (2.22)

\( (\lambda + G) \frac{\partial \varepsilon}{\partial z} + G \nabla^2 w + b_z = 0 \) \hspace{1cm} (2.23)

where \( G \) is the shear modulus and \( (\lambda) \) is a constant which are computed from Young’s modulus \( E \) and Poisson ratio \( (\nu) \) as follows:

\[
G = \frac{E}{2(1 + \nu)} \hspace{1cm} (2.24)
\]

\[
\lambda = \frac{\nu E}{(1 + \nu)(1 - 2\nu)} \hspace{1cm} (2.25)
\]

2.1.3 Deformation Equation For Linear Elastic Object

For a body being acted upon by external forces(f), the principle of conservation of momentum states that the rate of change of the total linear momentum of a given continuous medium equals the vector sum of all the external forces acting on the body, which results in the equation: [17, 53, 32]

\[
\nabla \cdot \sigma + \rho_0 f = \rho_0 \frac{\partial^2 u}{\partial t^2} \hspace{1cm} (2.26)
\]

In static case, it then becomes the equilibrium equation [17, 53] of stress:

\[
\nabla \cdot \sigma + \rho_0 f = 0 \hspace{1cm} (2.27)
\]

Finally from equations 2.18, 2.19, 2.20, 2.21, 2.22, 2.23, 2.26, 2.27 the dynamics of the elastic body is governed by the following partial differential equations:
\[
\rho_0 \frac{\partial^2 u}{\partial t^2} = (\lambda + G) \left( \frac{\partial^2 u}{\partial x^2} + \frac{\partial^2 v}{\partial y \partial x} + \frac{\partial^2 w}{\partial z \partial x} \right) + G \nabla^2 u + f_x
\] (2.28)

\[
\rho_0 \frac{\partial^2 v}{\partial t^2} = (\lambda + G) \left( \frac{\partial^2 u}{\partial x \partial y} + \frac{\partial^2 v}{\partial y^2} + \frac{\partial^2 w}{\partial z \partial y} \right) + G \nabla^2 v + f_y
\] (2.29)

\[
\rho_0 \frac{\partial^2 w}{\partial t^2} = (\lambda + G) \left( \frac{\partial^2 u}{\partial x \partial z} + \frac{\partial^2 v}{\partial y \partial z} + \frac{\partial^2 w}{\partial z^2} \right) + G \nabla^2 w + f_z
\] (2.30)

2.2 Physics Based Modelling

The face model incorporates a physical approximation to human facial tissue[47]. The intention is to approximate the elastic nature of the human skin tissues under a given load (facial expression). We also try to estimate change in the material properties of the human skin (whether modified by camouflage or make-up) based on the change in the strain pattern for a particular expression. In this study we investigate the force exerted and the resultant displacement of the facial tissues. The strain induced by activated muscle fibres in opening the mouth is studied. Basic physics is used to model the facial expression motion and introduces the computational methods for solving the resulting equations. This is an inverse problem wherein we know the displacements and try to recover the forces that are exerted.
CHAPTER 3
STRAIN COMPUTATION

3.1 Data Collection

The range data consisting of $x$, $y$, $z$ and the color images used for the study have been acquired using the Minolta VIVID 900 scanner which uses light stripe for triangulation. The scanner produces a laser beam which measures the position $(x,y)$ of each point of the subject along with the depth of that point with respect to the camera. The $z$ coordinate (depth) is measured from the camera to the point where the laser intersects the subject. In addition to the range data, the scanner also produces a 2D projection of the range data in the form of a RGB(color) image. The dataset comprises of 2 pairs of profile images for each subject under different lighting conditions; one with no illumination (OFF), and the other being with illumination (ON). The illumination source used in our study is a day light lamp to create varying illumination conditions for each subject. Each pair consists of two side-view images; one with a neutral face position (close-mouth) and the other with some facial expression (open-mouth). As a result, each subject has 4 images: closed mouth and open mouth under bright and low light.

The complete data set contains 62 subjects, from which we selected 50 subjects for the illumination 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 the other 12 subjects to see the effect of change in the strain pattern.
Figure 3.1. Profile Face Images Of A Subject Under Different Lighting Conditions
3.2 Computational Method

Since we deal with strain, which is related to displacements, we came up with a method to measure strain directly from the displacements. The information provided by the change in the depth value for the face across the open and close mouth frames does not affect the computation of the strain maps, because it depends on the relative displacements of two points on the face, which remains same with rigid motions of the face such as rotation and translation. Hence the effect of change in the z values can be ignored.

Based on the above assumptions, this approach is investigated, which deals with only the direct strains in the xy plane.

3.2.1 Theory Of Strain Using 2D Displacements

![Rigid Body Translation](image1)

![Rigid Body Rotation](image2)

![Deformation Of A Solid](image3)

Figure 3.2. Undeformed And Deformed Geometry Of A Solid

The total movement of a point with respect to a fixed reference coordinates is called *displacement*. Whereas the relative movement of a point with respect to another point
on the body is called deformation. In Figure 3.2 we see the effect of deformation on the solid. The analysis of deformation involves only geometric considerations and requires no assumptions regarding the material, except that it can be adequately modelled as a continuum[17]. We focus on the deformation in the xy plane only and define u and v to be components of displacement in the xy plane.

When a point O with coordinates (x, y) in an undeformed solid moves to the new position O' with coordinates (x', y'), where deformed coordinates are given as:

\[ x' = f(x, y); \quad y' = g(x, y) \]  \hspace{1cm} (3.1)

The resultant displacements can be equated as:

\[ x' = x + u; \quad y' = y + v \]  \hspace{1cm} (3.2)

Consider the deformation of a segment of a rod of infinitesimal length dx where end A moves to A' and end B moves to B', and the line segment A'B' now has a length dx' [17, 32]. The direct strain in the line segment A'B' is defined as:

\[ \varepsilon = \frac{dx' - dx}{dx} \]  \hspace{1cm} (3.3)

As discussed in section 2.1.1, Equation 2.9 , the three strain components as shown below [17, 32], together define the state of strain in any of the 2D planes (for ex. xy plane).

\[ \varepsilon_{xx} = \frac{\partial u}{\partial x}, \quad \varepsilon_{yy} = \frac{\partial v}{\partial y}, \quad \gamma_{xy} = \frac{\partial u}{\partial y} + \frac{\partial v}{\partial x} \]  \hspace{1cm} (3.4)

where \( (\varepsilon) \) is the direct strain.

Instead of describing the elastic deformation using higher order partial differentials, we restrict the computation to the first order differentials of the displacements u, v in the xy plane. Mathematically, the strain is proportional to the first derivative of the displacements and as shown in Figure 3.3 below:
Figure 3.3. From Displacements To Strain Map
The partial derivative with respect to one coordinate implies that the other coordinates are held constant during differentiation. If a displacement is taken as a function of one coordinate, then the partial derivative with respect to that coordinate will be equivalent to ordinary derivative [17, 32]. Hence

\[ \varepsilon_{xx} = \frac{du}{dx}(x) \]  

(3.5)

\[ \varepsilon_{yy} = \frac{dv}{dy}(y) \]  

(3.6)

\[ \varepsilon_{zz} = \frac{dw}{dz}(z) \]  

(3.7)

The displacement function can be approximated as the function as seen in Figure 3.4. The displacement derivatives are computed by finding the slope of the tangent of the displacement function using Finite Difference Approximation[17, 32]. Considering the X-axis to be the x coordinate and the Y-axis to be the displacement u in the X direction, the Forward difference approximates the slope of the tangent using the point ahead of point i as:

\[ (\varepsilon_{xx})_i = \frac{u_{i+1} - u_i}{x_{i+1} - x_i} \]  

(3.8)

Similarly the derivative in the y and z direction are computed by approximating the tangent in the Y and Z directions respectively as follows:

\[ (\varepsilon_{yy})_i = \frac{v_{i+1} - v_i}{y_{i+1} - y_i} \]  

(3.9)

\[ (\varepsilon_{zz})_i = \frac{w_{i+1} - w_i}{z_{i+1} - z_i} \]  

(3.10)
3.2.2 Algorithm

In this study to track the nonrigid elastic motion, we don’t use any explicit shape models, hence we rely on image features to track the motion. There are five major steps in determining the strain pattern which are as follows:

1. Feature Extraction.
2. Feature Correspondence.
3. Compute Feature Displacements.
5. Compute Strain.

3.2.2.1 Feature Extraction

A pixel qualifies for selection if it differs in intensity from amongst its neighboring pixels. Calculating the gradient values in the X and Y direction gives us the variation in
Figure 3.5. Strain Computation Using Derivative Of Motion Field
intensity along X or Y axis. If the variation is above the threshold, we claim it to be a feature point. To solve this problem, feature extraction is based on the computation of a gradient matrix within a window (w):

\[
g = \begin{bmatrix}
\sum_{w} \frac{\partial I}{\partial x} \frac{\partial I}{\partial x} & \sum_{w} \frac{\partial I}{\partial x} \frac{\partial I}{\partial y} \\
\sum_{w} \frac{\partial I}{\partial y} \frac{\partial I}{\partial x} & \sum_{w} \frac{\partial I}{\partial y} \frac{\partial I}{\partial y}
\end{bmatrix}
\]  

(3.11)

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):

\[
\frac{\partial I}{\partial x} = \frac{\partial G}{\partial x} * I
\]

(3.12)

\[
\frac{\partial I}{\partial y} = \frac{\partial G}{\partial y} * I
\]

(3.13)

The coefficients of all pixels inside w are then summed up to produce the gradient matrix. We then find the eigen values: (\(\lambda_1\), \(\lambda_2\)) for the 2x2 gradient matrix for each \(n \times n\) window. Given a threshold \(T\), satisfaction of condition:

\[
\min(\lambda_1, \lambda_2) > T
\]

(3.14)

suggests that the window contains a feature point. In our study we use a 9x9 window and predefined eigen value threshold (T) as 1.00. More details about the method can be found in [44, 54].

3.2.2.2 Feature Correspondence

Due to the nonrigid nature of face deformation, we presently establish correspondence between two frames manually to ensure the quality of displacement vector. For establishing correspondences, we first remove any possible rigid transformations between the two images; closed and open mouth. This is done by translating and rotating the pair of images
such that they are aligned along a fixed line. In this case the fixed line is the line joining the corner of the ear and the top of the nose intersecting with the forehead.

For ground truth purposes, some subjects were marked with lines running across their face as seen in Figure 3.6, to understand the exact motion of the displacement vectors. As seen in the Figure 3.6 the motion is remarkably seen in the lower jaw of the subject and insignificant motion in the upper jaw.

The region of interest is then marked following clockwise along the face contour, covering the entire area around the cheek. The boundary is followed simultaneously across both the images. Following the region extraction, then correspondences are established manually till sufficient points (around 70-80 correspondences) are gathered.

3.2.2.3 Pixel Interpolation of Displacements

After establishing correspondences, what we obtain are the displacements of the feature points which are discrete. To create a continuous displacement over the whole region we need to map the feature displacements to pixel displacements. This is done by interpolating the displacements of the nearest neighbors. All feature points within the circular radius of \((R_{TH})\) from the pixel are considered to compute displacements \((U_x, U_y)\). Each of these neighbors are then assigned weights \((w)\) depending on their distances \((d)\) from the pixel \((P)\). The farther the neighbor but within the radius, contributes lesser towards the pixel displacement. Figure 3.8 shows a diagrammatic representation of interpolating feature to pixel displacement. The features F1, F2, F3 contribute to pixel P1 in the increasing order of contribution.

3.2.2.4 Calculate Strain \((S_x, S_y)\) from \((U_x, U_y)\)

From the above pixel displacements \((U_x, U_y)\), we go a step further to calculate strain using equations 3.8 3.9 in the \(x, y\) directions. The strain map obtained may be slightly noisy and may not be a smooth surface. To overcome this, an averaging filter is used to
Figure 3.6. GroundTruth To Understand The Displacement Field
Figure 3.7. Facial Motion And Displacement Vectors
obtain a smooth strain map. The strain magnitude is calculated as follows.

\[ S_m = \sqrt{S_x^2 + S_y^2} \]  

(3.15)

where \((S_x, S_y)\) are strains in X, Y directions.
3.2.2.5 Normalize Strain Values

We use the standard principle component analysis (PCA) for similarity computation. We normalize the strain maps in the range 0-255 for intensity based PCA as shown below:

\[
\frac{e_x - e_{\text{min}}}{e_{\text{max}} - e_{\text{min}}} = \frac{I_x - I_{\text{min}}}{I_{\text{max}} - I_{\text{min}}}
\]  \hspace{1cm} (3.16)

where \((e_{\text{max}}, e_{\text{min}})\) 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. \((I_{\text{max}}, I_{\text{min}})\) are set to 255 and 0, respectively. Figures 3.10, Figures 3.11, Figures 3.12 show some of the strain maps under different lighting conditions.

From the strain patterns seen in Figures 3.13, Figures 3.14, we see that there is difference in the pattern generated for normal faces and those generated for taped faces.
Figure 3.10. Strain Maps Of Normal Faces Under Different Lighting Conditions
Figure 3.11. Strain Map Of A Normal Face

Figure 3.12. Strain Map Of A Modified Face
Figure 3.13. Strain Maps Of Normal Faces
Figure 3.14. Strain Maps Of Modified Faces
Figure 3.15. Mean Strain Map Of Normal Faces

Figure 3.16. Mean Strain Map Of Modified Faces
CHAPTER 4
FACE RECOGNITION AND IDENTIFICATION

4.1 Principal Components Analysis (PCA)

Considering face as a pattern, it is a complex as well as a challenging object to detect and recognize [26]. The face anatomy is rigid enough for people to have similar face structures but as an individual, there are color variations, in addition to the facial features. In addition to the above variations, there also arise variations due to expressions, cosmetics, facial hair, and glasses, which completely change an individual's appearance. Human visual pattern detection is the best, since it can take care of some intuitive factors, such as able to distinguish the same person with and without glasses, or the same person with some amount of makeup or the person seen under 2 different lighting conditions, which cannot be learnt by an algorithm.

Machine detection and recognition of human faces (patterns) is hence a complex problem due to the wide range of variations in the data [26]. To capture the principal biological and behavioral characteristics, we make use of Principal Component Analysis (PCA) or Eigen Faces. The eigen faces depict the features which carry the most information across a set of images. The machine detection understands these eigen faces and tries to identify a subject as a linear combination of the eigen vectors, since it is not feasible for the algorithm to capture every possible variation of a subject.

4.1.1 PCA Algorithms

PCA is a dimensionality reduction technique wherein the maximum variation in the dataset is maintained. The classification thus reduces from a higher dimension to a lower dimension called the eigen space, which is the space defined by the principal components.
or the eigenvectors of the data set. In the PCA technique research has been done for both fully automatic and partially automatic algorithms. Partially automatic algorithms are ones in which the coordinates of landmark points on the image are supplied to the normalization routine i.e. there is no automatic tracking of landmark points. In this study we use the partially automatic technique. There are four steps involved in the partially automatic eigen approach described in the following sections.

4.1.1.1 Preprocessing

1. Location of seed points. The PCA approach taken in this study is partially automatic. So we need to locate 2 seed points which are present in all the subjects in the dataset and which will be further used for normalization. In our study, for normalization of profile images, we use the top of the nose and the corner of the ear as our 2 points as seen in Figure 4.1 and for strain maps we choose 2 random points inside the strain map so as to cover most of the details as shown in Figure 4.1.

2. Geometric Normalization. In this step, the human chosen seed points are lined up across the subjects. We decide a 2 fixed locations (using the code) lx, ly, rx, ry, such that all the chosen seed points for all the subjects rest on these 2 fixed points. For aligning them translation, rotation and scaling are performed.

3. Masking. This is done to crop the (scaled and aligned from step2) image using a rectangular mask and the image borders such that only the face from the forehead to chin and ear to nose is visible. This is done to remove the unwanted areas such as hair, background etc. The mask for face/strain map is manually specified from the mean face/strain map image. In our case we used images of sizes 640x480 which were reduced to 200x250 pixels. For regular faces, a rectangular mask, and for strain maps an elliptical mask were used as seen in Figure 4.1
Figure 4.1. Geometric Normalization And Masking For PCA
4.1.1.2 Training

In the training phase, the algorithm learns from the given inputs. i.e. the eigenvalues and eigenvectors of the training set are extracted. The eigenvectors are chosen based on the top eigenvalues which represent the feature vectors which have the most variations across the images in the training set. The training set should preferably contain images which do not contain much of artifacts, such as spectacles, earrings, etc. and it should be a set of images that do not have any duplicates. After extracting the most significant vectors ($m$), the images are then projected into the eigen space of $m$ dimensions. Each image is represented as a linear combination of the $m$ eigen vectors in the reduced dimension.

4.1.1.3 Testing

The testing phase is where the algorithm is provided a set of known faces/strain maps known as the gallery set and a set of unknown faces/strain maps known as the probe set. The algorithm matches each probe to its possible identity in the gallery by computing the Euclidean distance between each probe and each of the gallery images.

4.1.1.4 Analysis

The performance of any biometric technique is measured by it’s:

1. Recognition Rate (Verification). Verification means that the system is trying to confirm that you are the one who you claim to be.

A verification system has to take the measurable features of the subject ($p$) and compare it against the known features of the person ($g$) who they are claiming to be, which makes it a one-to-one matching problem. The performance of the system is measured using 2 statistics, first is the probability of verification ($P_V$) i.e accepting that the probe $p$ is actually the person $g$ who he claims to be and second is the probability of false alarm ($P_F$) i.e reporting $p=g$ when $p\neq g$. The verification rate
is computed by:

\[
P_{V}^{c,i} = \begin{cases} 
0 & \text{if } |D_i| = 0 \\
\frac{|s_i(k) \leq c \text{ given } p_k \in D_i|}{|D_i|} & \text{otherwise,}
\end{cases}
\]

where

\[
P_{F}^{c,i} = \begin{cases} 
0 & \text{if } |F_i| = 0 \\
\frac{|s_i(k) \leq c \text{ given } p_k \in F_i|}{|F_i|} & \text{otherwise,}
\end{cases}
\]

where \(si(k)\) is the similarity measure[39]. Thus a pair of \((P_V, P_F)\) are generated for a given cut-off value \(c\). The cut off value is selected by varying between the minimum and maximum distances obtained after projecting all the probe images. By varying \(c\), different combinations of \((P_V, P_F)\) are produced. A plot of all \((P_V, P_F)\) is called the Relative Operating Characteristic (ROC).

2. Identification Power(Identification). Identification on the other hand is a one-to-many matching problem which is why it is a much more complex system. It means that given a subject (sample measurement) from the probe set, we are trying to find the closest match to it in our entire set of known identities in the gallery set. We report identification scores using the same number of probe and gallery. A plot of all the percentage of correct matches on the vertical axis and the Rank along the horizontal axis is called the Cumulative Match Scores Curve(CMC). The top rank match is at Rank 1 which indicates the fraction of probes correctly identified.
Figure 4.2. Match Example

Figure 4.3. Non Match Example
4.2 Experiments and Results

Experiments were carried out to see the effects of varying illuminations and facial expressions along with the changes in the subject’s appearance on the identification performance. The appearance changes were captured by application of stretchable tapes on the subject’s face. For every experiment a set of gallery and probe images were formed with different combinations of regular and modified faces under different illumination conditions as shown in Table 4.1.

<table>
<thead>
<tr>
<th>Exp.</th>
<th>Gallery</th>
<th>Probe</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>50 (RF, BL, CO)</td>
<td>50 (RF, LL, CO)</td>
</tr>
<tr>
<td>2</td>
<td>50 (RF, BL, ST)</td>
<td>50 (RF, LL, ST)</td>
</tr>
<tr>
<td>3</td>
<td>50 (RF+ST, BL, CO)</td>
<td>50 (RF+ST, LL, CO)</td>
</tr>
<tr>
<td>4</td>
<td>50(RF+ST, BL, CO)</td>
<td>50(RF+ST, LL, OO)</td>
</tr>
<tr>
<td>5</td>
<td>12 (MF, BL, ST)</td>
<td>12 (MF, LL, ST)</td>
</tr>
</tbody>
</table>

1. RF: Regular Face. MF: Modified Face.

2. BL: Bright Light. LL: Low Light.

3. CO: Close Mouth. OO: Open Mouth.

4. ST: Strain Map.

The following section provides the analysis of the important results obtained from the above experiments.
4.2.1 Experiment 1

The purpose of this experiment was to investigate the discrimination power of intensity based approach for regular faces under different illumination conditions. From the CMC curve shown in the Figure 4.4 it is seen that 93% of the population was identified correctly in the PCA space which makes it a promising biometric source. From the ROC curve for the experiment shown in the Figure 4.5, a verification rate of 99% was observed at a false alarm rate of 5%.

![CMC Profile Image](image1)

Figure 4.4. CMC-Profile Images Of 50 Subjects Showing The Identification Rate Of Illumination Variation For Closed Mouth

![ROC Profile Image](image2)

Figure 4.5. ROC-Profile Images Of 50 Subjects Showing The Identification Rate Of Illumination Variation For Closed Mouth
4.2.2 Experiment 2

The purpose of this experiment was to investigate the efficacy of strain maps in distinguishing the regular faces under different illumination conditions and expression changes. From the CMC curve shown in the Figure 4.6 it is seen that 76% of the population was identified correctly in the PCA space and from the ROC curve in Figure 4.7, a verification rate of 98% was observed at a false alarm rate of 5%.

![CMC-Curve](image1.png)

Figure 4.6. CMC-StrainMaps Of 50 Regular Subjects Showing The Performance Of The StrainMap Biometric Under Different Illumination Conditions

![ROC-Curve](image2.png)

Figure 4.7. ROC-StrainMaps Of 50 Regular Subjects Showing The Performance Of The StrainMap Biometric Under Different Illumination Conditions
4.2.2.1 Averaging ROC Curves

The ROC seen in Figure 4.7 is the plot of true(Tp) and false positives(Fp) by thresholding the distance matrix obtained after projecting the probe into the eigen space. The threshold is decided between the minimum and maximum distance along the distance matrix diagonal(which indicates the match cases). We go a step ahead to obtain a cross-validated ROC curve. The different test folds for which a ROC is plotted is got by dropping one subject at a time, i.e. we reduce the distance matrix dimensionality by one. We have 50 subjects, so we get 50 test folds in which a single subject is dropped, resulting in the distance matrix of size 49x49. The 50 test fold ROCs are seen in Figure 4.8.

![ROC Using Only Diagonal Thresholds For 50 Subjects](image)

**Figure 4.8. ROC Curves For The Strainmap Biometric From 50 Test Samples**

After the 50 test samples are plotted, we then combine all test folds with the match and non-match scores for each instance, and draw a single ROC curve as seen in Figure 4.9.
To obtain ROC curve with error bars, we resample the false positives with the interval size of 0.001 across all the test folds. At each resampled Fp, the true positives are averaged. The plot of the this fixed Fp and the average Tp results in mean ROC as seen in Figure 4.9.

Figure 4.9. ROC Curve From Combining The 50 Test Samples

Figure 4.10. ROC Curve Obtained By Vertical Averaging The True Positives At A Sampled False Positive

47
We then compute the error bars from the mean ROC to the minimum and maximum test fold value at the fixed Fp as seen in Figure 4.10.

### 4.2.3 Experiment 3

![Profile Plus Strain Map](image1.png) + ![Input To PCA For Multi-Classifier Test](image2.png) =![Profile Plus Strain Map](image3.png)

**Figure 4.11. MultiClassifier: Profile Plus Strain Map**

The goal of this experiment is to find out the effectiveness of strain maps and intensity as a combined biometric on the identification and verification performance. The combination technique used is quite simple as seen in Figure 4.11.

The input image is a combination of the regular intensity face and strain map of the same subject captured during the face expression.

The CMC (Figure 4.12) and the ROC (Figure 4.13) for this experiment show that there is an increase in the identification and the verification rates as compared to the performances of the two biometrics taken individually.

#### 4.2.3.1 Analysis

Figure 4.14 combines the results of Experiments 1, 2 and 3 to provide a clear distinction between one biometric source over the other.
Figure 4.12. CMC-Maps Of 50 Regular Subjects Showing The Performance Of The Multi Classifier - Strain Plus Intensity

Figure 4.13. ROC-Maps Of 50 Regular Subjects Showing The Performance Of The Multi Classifier - Strain Plus Intensity

From Figure 4.14 and Table 4.3, it is evident that when only facial strain map is used for identification, the accuracy is lower than that of intensity based face recognition, because of the availability of more features on the face in the later case. More number of features result in more variations across the set of images, thereby giving an ability to distinguish the faces easily.

The face plus strain map is slightly better than the individual face or the strain map. The reason is, the strain map may be able to add information to the combined technique to make it better, however, does not have enough information by itself to give very good results. For example, the strain map technique may result in poor recognition rate, if the
expression changes for a person. In this case, the intensity compensates for the decrease. Similarly, intensity-based face recognition could suffer from unstable conditions such as illumination changes or application of artifacts, etc., in which case the strain map may be able to add information and the combined technique gives better results. Thus, both the biometrics have the capability to aid each other in situations when the individual biometric may fail.

From the above 3 experiments conducted in this research, we can assert that the strain-based technique is robust and invariant to the illumination changes. A performance analysis of the classification power of the strain maps shown in the Figure 4.15 reaffirms the above conclusion. The Figure 4.15(a,b) shows that with the strain, the overlap between the match and the non-match classes is less as compared to the intensity. The combined biometric source has again proved to be a better classifier as shown in the Figure 4.15(c).
Table 4.2. Top Ten Ranks Of Identification For Normal Intensity Faces, Strain Of Normal Faces, And Of (Strain+Normal) Faces

<table>
<thead>
<tr>
<th>Rank</th>
<th>Probability Of Correct Match</th>
<th>Intensity Normal</th>
<th>Strain Normal</th>
<th>(Intensity + Strain) Normal</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0.92</td>
<td>0.76</td>
<td>0.97</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>0.96</td>
<td>0.9</td>
<td>0.98</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>0.98</td>
<td>0.96</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>1.00</td>
<td>0.96</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>1.00</td>
<td>0.96</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>1.00</td>
<td>0.96</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>1.00</td>
<td>0.96</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>1.00</td>
<td>0.96</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>1.00</td>
<td>0.96</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>1.00</td>
<td>0.96</td>
<td>1.00</td>
<td></td>
</tr>
</tbody>
</table>
Figure 4.15. Distribution Of The Match And No-Match Class. a. Intensity Normal Faces  b. Strain Normal Faces  c. Strain+Intensity Normal Faces
4.2.4 Experiment 4

The goal of this experiment is to determine whether the strain map can help in improving the identification rate of the multi classifier in cases where intensity fails. This experiment was conducted in two parts. In the first part intensity was used for the identification for change in expression as well as illumination changes. The result of this part of the experiment is shown in the Figure 4.16.

![Figure 4.16. CMC-Profile Images Of 50 Subjects Showing The Identification Rate For Expression Change(Closed Mouth v/s Open Mouth)](image)

![Figure 4.17. ROC-Profile Images Of 50 Subjects Showing The Identification Rate For Expression Change(Closed Mouth v/s Open Mouth)](image)
In the second part of the experiment the strain map (different illumination) is combined with the intensity (different expression) under different illumination conditions. The result shown in the Figure 4.18 shows that the overall identification rate increases over the intensity based approach. This increase in the identification and verification rate can be attributed to the contribution made by the strain map in cases in which the intensity biometric fails.

![CMC graph](image1)

**Figure 4.18.** CMC-Combined Biometric Of Strain And Intensity For 50 Subjects For Different Expression And Different Illumination Condition

![ROC graph](image2)

**Figure 4.19.** ROC-Combined Biometric Of Strain And Intensity For 50 Subjects For Different Expression And Different Illumination Condition
4.2.4.1 Analysis

Figure 4.20 combines the results of Experiments 2 and 4 to provide a clear distinction between one biometric source over the other.

![CMC Graph]

Figure 4.20. CMC-Identification Performance Of Intensity Different Expression, Strain Map Different Illumination, And Face+Strain Map Concatenated Biometrics
Table 4.3. Top Ten Ranks Of Identification For Different Expression Intensity Normal Faces, Strain Of Normal Faces Under Different Illumination, And Of (Strain+Intensity) Faces

<table>
<thead>
<tr>
<th>Rank</th>
<th>Probability Of Correct Match</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Intensity Normal</td>
</tr>
<tr>
<td>0</td>
<td>0.60</td>
</tr>
<tr>
<td>1</td>
<td>0.74</td>
</tr>
<tr>
<td>2</td>
<td>0.82</td>
</tr>
<tr>
<td>3</td>
<td>0.84</td>
</tr>
<tr>
<td>4</td>
<td>0.88</td>
</tr>
<tr>
<td>5</td>
<td>0.88</td>
</tr>
<tr>
<td>6</td>
<td>0.94</td>
</tr>
<tr>
<td>7</td>
<td>0.96</td>
</tr>
<tr>
<td>8</td>
<td>0.96</td>
</tr>
<tr>
<td>9</td>
<td>0.98</td>
</tr>
</tbody>
</table>

Figure 4.21. Distribution Of The Match And No-Match Class. a.Intensity Normal Faces Different Expression  c.Strain+Intensity Normal Faces Different Expression Different Illumination
4.2.5 Experiment 5

This experiment was performed to see the effect of modifications to the regular faces on the performance of identification using strain maps. The CMC (Figure 4.22) in this case, shows a correct identification rate of 83% which suggests that a person who changed his appearance by makeup or plastic surgery has a better chance to be detected. By putting a tape on the subject’s face we tried to modify the property changes of facial tissues which is hard to detect using the methods based on visible cues. Although the data set used was quite small (12 subjects only) the performance is still quite promising with the verification rate of 84% at false alarm rate of 5% as shown in ROC Figure 4.23.

Figure 4.22. CMC-StrainMaps Of 12 Modified Subjects Showing The Performance Of The StrainMap Biometric Under Different Illumination Conditions

Figure 4.23. ROC-StrainMaps Of 12 Modified Subjects Showing The Performance Of The StrainMap Biometric Under Different Illumination Conditions
CHAPTER 5
CONCLUSION AND FUTURE WORK

5.1 Conclusion

A new face recognition method is proposed that utilizes the elastic strain pattern computed from the observed face motion. The rationale 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 biometrics goes beyond the visible cues and is more reliable in the presence of camouflage such as make-up and surgery, because it deals with the displacement field caused from the facial expression.

Strain maps are generated using displacements and their derivatives as per the definition of strain. It is worth noting that the strain maps are generated using only one facial expression. The mean strain map indicates that each individual exhibits a similar strain map under same facial expression.

The experiments and the results suggest that the strain maps of modified faces is more unique than the strain map of normal faces which makes the recognition of modified faces better even if they are mixed with the normal faces population.

The use of the combined biometrics of intensity image and strain map of the face shows a considerable increase in the identification rates than that of intensity image and strain map separately.

The strain map may be sensitive to the changes in the facial expressions. But it is consistent with any given single expression. For example, strain map generated for the smiling expression will differ greatly from its counterpart generated as a result of opening the mouth because of variations in the displacements.
5.2 Future Work

For further testing a larger data set is needed to thoroughly evaluate the performance. Secondly, manual correspondence matching is used which needs to be automated. Optical flow and motion measurement in video sequence also could be considered for predicting the motion. Finally the 3D strain model of the whole face could be built to see if the range data helps in computing strain.
REFERENCES


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