ROBUST FACIAL RECOGNITION WITH MULTIMODAL FUSION

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ABSTRACT: Physical and behavioral traits are used in biometrics to identify people. The main components of biometrics are identification and verification. If biometric data matches a claimed ID template, proof is complete. Biometric data can be compared to a stored pattern to verify identity. Previous studies used 2D and 3D facial recognition. More thorough composite matching is used in addition to feature-based matching. Hotelling transform changed the 3D face's texture and placement. SIFT and 3D SFR are used in rejection predictors. Before classifying known faces as distinctive, it must eliminate several choices. A Face Recognition System that can identify people by their face structure in a specific setting is the project's goal. A case study and several basic Matlab tests show that a multimodality technique employing 2D and 3D facial representation can identify faces. The validation index calculates facial recognition performance from erroneous acceptance and rejection rates.
Keywords: Biometrics, face recognition, spherical face representation, SIFT, ICP

1. INTRODUCTION

Facial recognition is easy, universal, and unique. Concerns regarding possible human reactions make biometric identification methods like fingerprinting and iris scanning either unsuitable or impossible. The enormous variety of human faces, together with the many ways in which variables like gender, age, environment, and cosmetics can alter one's appearance, makes face identification an especially challenging task. The field of biometrics focuses on identifying individuals by observable psychological or behavioral traits.
It is common practice to divide biometric applications into two categories. You can see the identification and proof modes in Figure 1. The verification process involves checking a person's identity against a database of previously verified identities using their biometric data. Forms that are comparable include user IDs, smart cards, and user names. A method of providing evidence is to draw comparisons. "Positive recognition" programs frequently use verification mode.

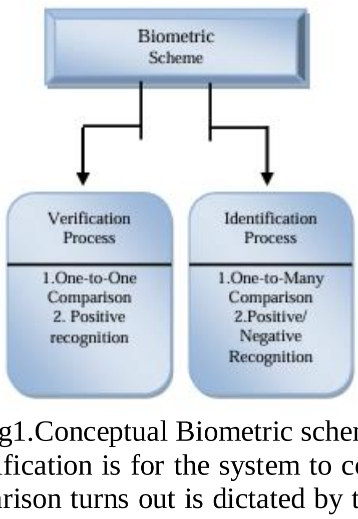

Fig1.Conceptual Biometric scheme

The initial step in a person's accurate identification is for the system to compare their biometric data with a database template of all the names. How the comparison turns out is dictated by the threshold value. The process is deemed effective if the outcomes of comparing biometric data to a previously stored template are within a specific range. A lot of people use the identification option for "positive recognition" and "negative recognition."

2. LITERATURE REVIEW

Whenever older face recognition systems use low-resolution images, they mix them together and lose some of the subtle differences between faces. The multi-tiered architecture for high-resolution face recognition in this study is based on geometric signals. Each face image is made up of separate parts, such as the basic look, the facial organs, the top layer of skin, and any unusual traits. A lot of different feature matching algorithms have been offered as ways to do this. The algorithms are limited in many ways, including the types of problems they can solve, the speed at which they can solve them, how well they handle changes in sharpness, and how selective the traits they use are. This paper presents a new feature-matching method for automatically aligning range shots. The problems with earlier methods have been fixed by this solution.

People have pushed for face recognition tools in a number of different ways. Some examples are recognizing faces from 3D pictures, recognizing faces using more than one modality, and pretreatment methods that take into account lighting and other factors in the environment. The main focus of this study is the Face Recognition Vendor Test (FRVT).

Current 2D face recognition algorithms have trouble when there are big changes to the face, like when the lighting, expression, or position of the head shift. On the other hand, they work very well when everything is controlled. Three-dimensional information about the face helps with recognition because the face is both a three-dimensional shape and a two-dimensional picture that can adapt to these changes. This study shows how the Geometrix Face Vision3D technology can recognize facial traits by using texture and geometry. The main goal of this project is to make a multimodal hybrid face recognition system. We look at the FRGC v1.0 numbers to see how well this method works. Our method, which combines holistic and model-based matching, consistently produces results when we compare three-dimensional traits. Holistic matching is the only way to match 2D facial traits.

The piece explains a way to find repeating elements in pictures that can be used to contrast and compare different points of view. The term SIFT, which stands for Transform Scale Invariant Features, is a good way to describe this method. From reference pictures, SIFT descriptors are made and then stored in a database so that images can be matched and recognized. To find pairs of pixels that match, the Euclidean distance is used between each pixel in a new picture and each pixel in the database. This study looks into how well nearest-neighbor algorithms work when they are used to do these kinds of calculations on big databases.

A lot of things, like the subject's stance and the amount of light, can affect 2D photo face recognition systems. It works better for the face recognition system in this study when three-dimensional shape data is used in a range of lighting and orientation situations. At each stage, a 3D model of the face is made by putting together several 2.5D pictures of the real face. This work talks about an independent 3D face recognition method. This part talks about a number of interesting discoveries. With these technologies, 3D faces can be automatically recognized, their locations can be adjusted and made more normal, a spherical face image can be used as a rejection predictor, and facial expressions can be managed correctly.

This study is about the multi-view correspondence technique, which includes finding possible matches in a 4D hash table. This way makes it easier to connect the random 2.5D views of a free-form object mechanically. The end result is a spanning tree that is not in any particular order and shows how the differences are spread across all viewpoints. After that, a single coordinate system is usually used to line up the branches. With multi-view fine registration, the registration process can be made better, and the separate photos can be put together to make a 3D model that makes sense.

Texturing in two dimensions or adding infrared data to geometry in three dimensions are two examples of multimodal methods. Most of these projects don't look at facial emotions because they only use small datasets. In this study, wavelet analysis was used to separate a simple biological profile from large datasets. This lets research happen across borders and within regions. Both 2D and 3D data need to be normalized in different ways. Also, images need to be normalized for edge-based and principal component analysis methods to work. For the ICP-based method, this amount of accuracy is not needed. There are detailed normative directions given.

3. FEATURE BASED MULTI MODAL FACE RECOGNITION (FBMFRS)

A technique for comparing and recognizing characteristics in 2D and 3D formats was suggested in the study. To get to this result, we used a method that combined feature-based and holistic assessments. A 3D face's texture and location can be adjusted by applying the hotelling transform to a single, easily-recognizable point. The Scale Invariant Feature Transform (SIFT) and the 3D Spherical Face Representation (SFR) models are combined to build a rejection classifier. Spin and tensor pictures are what set SFR apart from competing 3D models. When considering the processing cost, SFR outperforms spin and tensor images as a rejector.

Spherical Face Representation and Rejection classifier (SFR)

Although the sphere-based facial picture and the rejection classifier are both crucial, they can complement or counteract each other depending on the situation. An easy way to eliminate many possible classes and characteristics is to improve a rejection classifier for a high Success for Rejection (SFR). Finding larger display places quickly becomes easier with this. This algorithm can be used to evaluate how well a rejection predictor works.

DOI:10.48047/intjecse/v15i4.104 ISSN: 1308-5581 Vol 15, Issue 04 2023

$$\text{Perf}(\mu) = \quad P_{a \in S}(\mu(a))G \quad \text{..........(eqn 1)}$$

Class names are returned by the S function, while the gallery's height and width are controlled by the G method. Compared to the brute force matching method, the rejection classifier methodology achieves a much lower comparison threshold of only 0.03%. The remaining characteristics were checked using a technique that pairs areas according to their articulation difficulty level. Because the segmented eyes, forehead, and nose were less sensitive, the Iterative Closest Point (ICP) approach was used to find the best match. The results of all matching search techniques are aggregated at the metric level to improve precision.

The outcomes are assessed using the benchmark data from FRGC v2.0. The multimodal hybrid algorithm achieved the best results compared to the others, with a proof rate of 99.74% and a false acceptance rate (FAR) of 0.001. Its success percentage was 95.37% for questions with non-neutral terms and 99.02% for queries with neutral ones.

Using a database of known profiles, a face recognition system can extract and compare a person's facial traits to identify them. Using a matching technique, this paper explores the development of a face recognition system that can identify previously viewed faces. The comparison technique can be carried out using the current facial dataset. Combining 2D and 3D data, we have created a face recognition system. In addition, we have included a hybrid matching approach that considers both holistic and feature-based criteria.

Feature based Multimodal Face Recognition System Architecture

Our projected project's architectural model is shown in Figure 2. A feature-based multimodal face recognition system goes through four separate phases. At the beginning, there is facial recognition.

It is feasible to distinguish between people based on their looks by using methods like feature consistency and template matching. Its goal is to detect static face features by removing unnecessary pixels based on their geometric interpretation. The term "template matching" refers to a method of finding similar images by comparing them to published examples.

Important face features including the eyes, jawline, and nose are located using the branch and bound technique. Achieving the lowest feasible classification error is accomplished by reducing the number of dimensions and processing time through this approach.

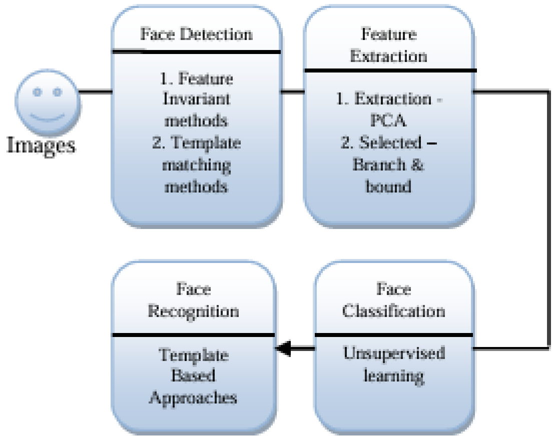

Fig2. Architecture of Feature based Multimodal Face Recognition System

Third, for accurate face classification, we use unsupervised learning and an exclusive k-means clustering method. As a last step, we use a template-based face recognition algorithm to find unique traits by comparing the photos to a database of popular templates.

Feature Extracted Multimodal Face Recognition System– Algorithm

- Identifying people in the given image is the primary goal at this stage.
- Second, you must use techniques that are independent of the faces' position and orientation if you want to succeed in face identification.
- The provided images are then compared to the stored feature patterns through the use of template matching techniques.
- Third, apply Principal Component Analysis (PCA) to the features while keeping in mind the feature extraction approach you've chosen.
  Step 3.1 uses the branch-and-bound algorithm to simplify the shape and size estimation of the eyes, nose, and jaw.
- Using an improved k-means clustering method is the fourth step in the unsupervised learning process for face classification. The fifth step involves using template-based strategies to match features.

DOI:10.48047/intjecse/v15i4.104 ISSN: 1308-5581 Vol 15, Issue 04 2023

4. EXPERIMENTAL RESULTS AND DISCUSSION

The results of the research presented in this article show that a hybrid multimodal 2D-3D strategy is effective for automatic face recognition. We are now testing spin images and SFR to see how well they perform as rejection classifiers. In the experiments, neutral and non-neutral expressions were used. However, SFR worked better with probes that showed a non-neutral expression, while spin images worked better with probes that showed a neutral expression.

When compared to the SFR-based classifier, the spin image classifier clearly loses out. Building and matching an SFR of a probe and rejecting a gallery selection took 6.2 ms on a 2.3 GHz Pentium IV CPU according to Matlab. It took 2,363 milliseconds to generate a rotational image.

The False Acceptance Rate (FAR) and the False Rejection Rate (FRR) are calculated by researchers to assess the performance of a feature-based multimodal face recognition system. You may find the FAR and FRR values by using Equations 2 and 3. Figure 3 shows the False Acceptance Rates for MFRS and FBMFRS.

$$FAR = \frac{\text{Number of images accepted} * 100}{\text{Number of images tested}} \quad \text{......(eqn 2)}$$

$$FRR = \frac{\text{No. of original images rejected} * 100}{\text{No. of original images tested}} \quad \text{......(eqn}$$

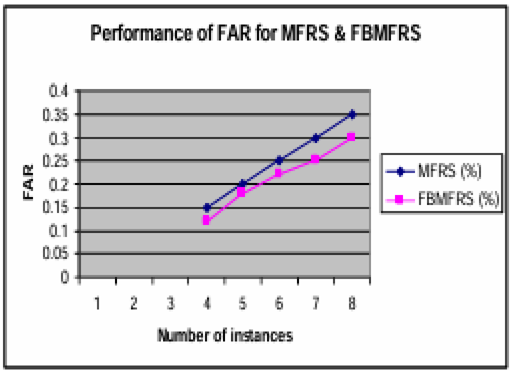

Fig3. Performance of FAR for multimodal face recognition and feature based multimodal face recognition systems.

An upward correlation between the overall case count and the MFRS False Acceptance Rate (FAR) is shown in Figure 3. However, when compared to the state of the art, the FAR for FBMFRS performs better. A reduced false acceptance rate (FAR) is an outcome of FBMFRS's simplicity compared to MFRS.

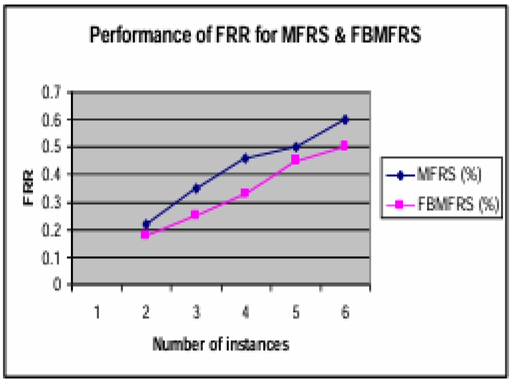

Fig 4. Performance of FRR for multimodal face recognition and feature based multimodal face recognition systems.

Multimodal face recognition's false rejection rate as a function of training model count is shown in Figure 4. You can see the False Rejection Rate on the Y-axis and the quantity of training templates on the X-axis.

5. CONCLUSION

The accompanying image shows the performance of the False Acceptance Rate and False Rejection Rate on many industry-standard facial recognition data sets. Famous people's eyes, cheekbones, and jawlines served as inspiration for these models. The branch and bound feature selection approach and location-and angle-invariant feature invariant procedures are all part of our ideas.

DOI:10.48047/intjecse/v15i4.104 ISSN: 1308-5581 Vol 15, Issue 04 2023

In order to test how well the strategy worked, we used 256 by 256 pixel photos. When compared to the Feature Based Multimodal Face Recognition System, the MFRS achieves a lower False Acceptance Rate (FAR) of 1.05% and a lower False Rejection Rate (FRR) of 1.25%. The challenge is so diminished.

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