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OPTIMIZING FACIAL RECOGNITION WITH MULTIMODAL FEATURE FUSION IN MULTI-VARIANT FACE ACQUISITION TECHNOLOGIES

#1Kumbarkari Vineeth, Department of ECE,
#2Dr. P.Saiprasad, Professor, Department of ECE,
Ballari Institute of Technology & Management(Autonomus) ,Ballari, Karnataka.
Corresponding Author: Kumbarkarivineeth@gmail.com

ABSTRACT: Biometrics can confirm an individual's identity by using their unique physical and behavioral characteristics. The primary elements of this process are identification and verification. When biometric information is compared to a stored template of the claimed identity, the verification procedure is considered successful. In a face recognition investigation, composite matching enabled researchers to merge 2D and 3D data, increasing the accuracy of identification. To increase recognition, we altered the texture and placement of the 3D face using the Hotelling transform. The accuracy of face identification was increased by using a rejection classifier that uses SIFT and SFR features to filter out less promising applicants. In several cases, the program was able to identify individuals based only on the geometry of their faces by using a multimodal method. Matlab testing revealed that face discrimination was much improved by combining 2D and 3D techniques. The accuracy was assessed using a validation index that includes the rates of false rejection and false acceptance. If used, this new technique could enhance facial recognition software.

Keywords: Biometrics, Face Recognition, Spherical Face Representation, SIFT, ICP.

1. INTRODUCTION

Face recognition is practical, covert, and available all across the world. Biometric identification technologies are inappropriate due to concerns over human reactions to them. The vast variety of human traits, as well as the many ways in which gender, age, environment, and cosmetic procedures can impact an individual's look, makes face identification a difficult task.

Biometrics seeks to develop identification methods that rely on observable mental or behavioral characteristics.

Biometrics is mostly used for two purposes. The possibilities for identification and evidence are displayed in Figure 1. A person's identification can be confirmed by comparing their biometric data with a database of known identities. This class includes things like identities, smart cards, and user IDs. Using analogies is a valid way to convey proof. There are instances where "positive recognition" is used in verification mode.

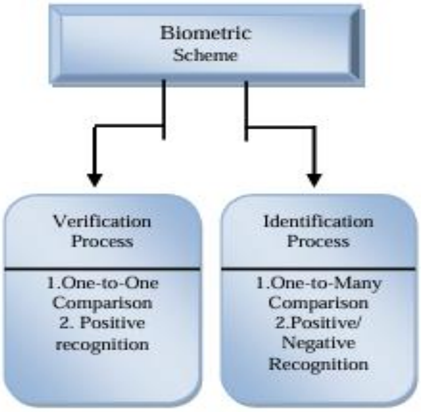

Fig 1. Conceptual Biometric scheme

The initial step in a person's successful identification is for the system to match their biometric data with a database template of all the names. Specifying a threshold value determines how the comparison will turn out. It will be successful if the comparison of the biometric data to a saved template stays within a preset range. Identification is commonly used for "positive recognition" or "negative recognition."

2. LITERATURE REVIEW

Low-resolution pictures cause older face recognition systems to lose subtle variations between people's characteristics. For high-resolution face detection using geometric features, we provide a multi-tiered architecture in this paper. Each depiction of a face consists of four distinct parts: the outer layer of skin, any noteworthy features, the general look, and the facial organs. Various feature matching strategies have been suggested to achieve this objective. The algorithms have limits in terms of the kinds of problems they can solve, the speed with which they do so, their resilience to changes in sharpness, and the discriminatory power of the features they employ. To automatically align range photos, we present a novel feature matching method in this study. The flaws in the prior methods are addressed by this method.

There are a lot of new ideas for face recognition systems. Techniques such as multi-modal face recognition, 3D face identification, and pretreatment algorithms that consider illumination and ambient variables are only a few examples. The FRVT, or Face Recognition Vendor Test, is the center of this investigation.

Although current 2D face recognition algorithms work admirably in controlled environments, they become severely challenged when confronted with substantial changes to the face, such as those caused by changes in lighting, expression, or head tilt. Since a human face is both a three-dimensional shape and a two-dimensional image, it can respond to the aforementioned changes, which is why 3D facial information is useful for face identification. This research shows that the geometrix Face Vision3D system can identify features using texture as well as shape. This work primarily aims to develop an algorithm for multimodal hybrid face recognition. In order to determine how well this strategy works, we look at the FRGC v1.0 data. In order to achieve precise results when comparing three-dimensional faces, our approach integrates model-based matching with holistic matching. Holistic matching is the sole method employed for 2D face features.

Finding repeating components in photographs to compare and contrast different perspectives is made easier by the study's methodology. One appropriate acronym for this approach is SIFT, which stands for scale-invariant feature transform. The creation of SIFT descriptors from reference images is done and then saved in a database for use in image recognition and matching. A new image's pixel-to-database distance is calculated using the standard formula, and matching pixel pairs are selected according to this distance. The paper delves into the topic of developing efficient nearest-neighbor algorithms that can execute this type of calculation on massive databases with ease and speed.

The accuracy of 2D photo face recognition algorithms is affected by a number of factors, including the subject's lighting and posture. In order to increase its performance under diverse illumination and orientation settings, the face recognition system in this study makes use of three-dimensional shape data. Each step involves building a 3D model of the face from a series of 2.5D images. The manuscript details a method that can detect three-dimensional faces automatically. In this article, numerous significant discoveries are offered. With the help of these technologies, it is possible to automatically detect 3D features, fix and normalize their arrangement, use a spherical model of the face as a rejection predictor, and appropriately handle facial expressions.

The multi-view correspondence method, which searches a 4D hash database for potential matches, is the center of the research. A free-form object's disordered 2.5D perspectives can be mechanically connected using this method. The final product is a spanning tree of relative changes across all the viewpoints, which is not ordered. The next step is to align the branches using a single coordinate system. Using multi-view fine registration, it is possible to enhance the registration process and reassemble the individual photographs into a unified 3D model.

By combining two-dimensional geometry with two-dimensional infrared or textural data, multimodal approaches provide a more complete picture. The majority of these endeavors fail to consider facial expressions because they rely on tiny datasets. This research uses wavelet analysis to get a concise biometric profile from massive datasets. This paves the way for study on a national and even international scale. There are distinct normalizing procedures needed for 2D and 3D data. Principal component analysis and edge-based approaches also make use of normalized images. In the case of the ICP-based approach, such precision is superfluous. We offer thorough normative guidelines.

3. FEATURE BASED MULTIMODALFACE RECOGNITION (FBMFRS)

The study suggested a method for finding and comparing features in both 2D and 3D formats. The method that yielded this result was a hybrid of feature-based and holistic assessments. Applying the hotelling transform to a single easily-recognizable point can change the location and texture of a 3D face. The Scale Invariant Feature Transform (SIFT) and 3D Spherical Face Representation (SFR) models are used to develop a rejection classifier. The use of spin and tensor images distinguishes SFR from competing 3D models. Superior to spin and tensor images as a rejector in terms of processing cost is SFR.

SPHERICAL FACE REPRESENTATION ANDREJECTION CLASSIFIER (SFR)

The rejection classifier and the sphere-based face picture are both vital, but they could work in tandem or against one another. With a rejection classifier calibrated for a high Success for

Rejection (SFR), a huge number of potential classes and faces can be efficiently purged. This allows for the faster discovery of larger exhibition spaces. This method can be used to determine how effective a rejection predictor is.

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

Gallery dimensions can be specified using the G method, while class names can be obtained using the S method. By a margin of only 0.03%, the rejection classifier technique outperforms brute force matching. An area-articulation difficulty method was used to validate the remaining characteristics. The Iterative Closest Point (ICP) method was employed to discover the best match due to the decreased sensitivity of the segmented eye, forehead, and nostril. Accuracy is enhanced by including all pertinent search technique results at the metric level. Findings are evaluated with the help of FRGC v2.0 reference data. With the best results (99.74% proof rate and 0.001% FAR), the multimodal hybrid method was used. There was a success rate of 99.02% for neutral phrases and 95.37% for non-neutral terms.

A facial recognition system can positively identify a person by comparing their photo to a database of previously identified faces. The goal of this project is to develop a system for facial recognition that can successfully match images with known characteristics. It is possible to conduct comparisons using the facial dataset. Our system streamlines facial identification by combining 2D and 3D data. In addition, we employ a hybrid matching method that takes both comprehensive and feature-based criteria into account.

FEATURE BASED MULTIMODAL FACE RECOGNITION SYSTEM ARCHITECTURE

The architectural model of our proposed project is shown in Figure 2. Multimodal face recognition based on features entails four stages. Facial recognition is one of the first steps.

People can be identified based on their facial features using template matching and feature consistency. In order to identify fixed facial features, it uses geometric interpretation to filter out extraneous pixels. Image similarities to known samples can be discovered by template matching. Eye, nose, and jawline recognition is within the scope of the branch and bound approach. In order to achieve the best possible classification accuracy, this method minimizes processing time and dimensionality.

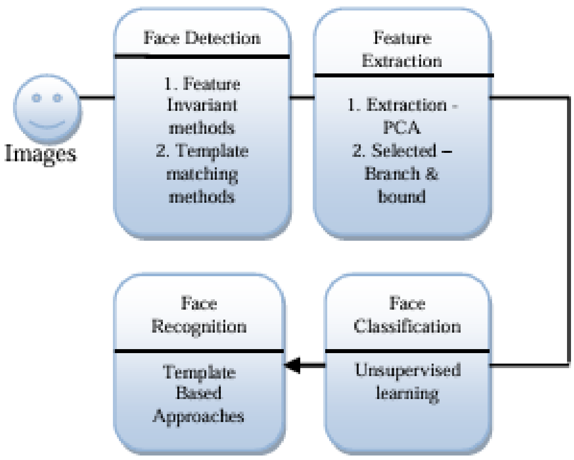

Fig 2. Architecture of Feature based Multimodal Face Recognition System

Third, via unsupervised learning and a novel k-means clustering approach, we successfully categorize faces into their respective categories. Lastly, a template-based face recognition algorithm is used to compare photographs to a library of known templates, which act as distinguishing traits.

FEATURE EXTRACTED MULTIMODAL FACE RECOGNITION SYSTEM – ALGORITHM

- It all starts with identifying people in the provided picture.
- After that, you should use techniques that don't care about the direction or location of the features you want to find.
- The following stage involves utilizing template matching techniques to compare the provided photographs with the previously saved feature patterns.
- Third, run Principal Component Analysis (PCA) on the features using the feature extraction approach you've chosen.
- The size and simplified shape of the jaw, nose, and eyes are estimated in Step 3.1 using the branch-and-bound technique.
- Step four of the unsupervised learning process involves using an upgraded k-means clustering algorithm for face categorization.
- The features are subjected to a template matching procedure utilizing template-based approaches in the fifth stage.

3. EXPERIMENTAL RESULTS AND DISCUSSION

An effective hybrid multimodal 2D-3D approach for automatic face recognition is demonstrated by the experiments conducted in this paper. At the moment, researchers are testing how well spin images and SFR perform as rejection classifiers. The investigations made use of both neutral and non-neutral terms. Nonetheless, spin pictures were more effective when the probes displayed a neutral expression, but SFR worked better when the probes displayed an expression other than neutrality.

The classifier findings demonstrate that the SFR-based classifier outperforms the spin image classifier. Matlab required 6.2 milliseconds on a 2.3 GHz Pentium IV CPU to construct and match a probe's SFR and reject an option from the gallery. Making a spinning picture required 2,363 milliseconds.

To measure how well a feature-based multimodal face recognition system works, researchers calculate the False Acceptance Rate (FAR) and the False Rejection Rate (FRR). Equations 2 and 3 provide the values for FAR and FRR. The MFRS and FBMFRS false acceptance rates are displayed in Figure 3.

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

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

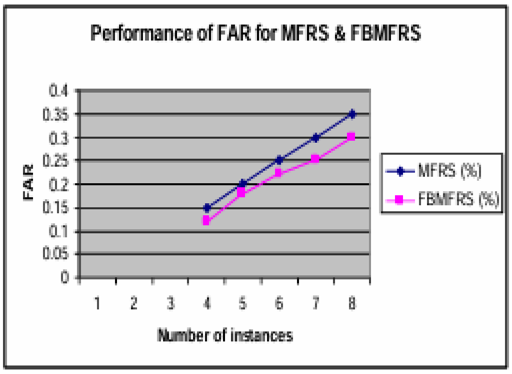

Fig 3. Performance of FAR for multimodal face recognition and feature based multimodal face recognition systems.

As shown in Figure 3, there is a positive correlation between the total number of instances and the MFRS False Acceptance Rate (FAR). As a result of its simplification, FBMFRS has a lower false acceptance rate (FAR) than MFRS; yet, it surpasses the benchmark.

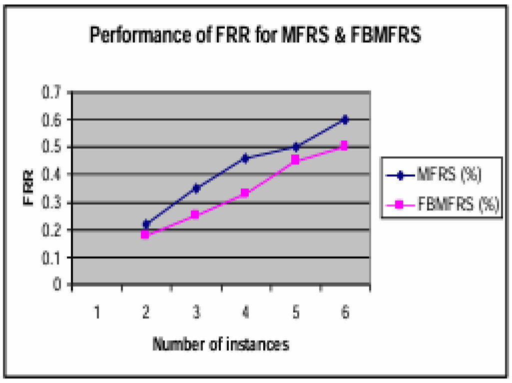

Fig 4. Performance of FRR for multimodal face recognition and feature based multimodal face recognition systems.

In Multimodal Face Recognition, the False Rejection Rate is affected by the number of training models, as shown in Figure 4. The False Rejection Rate is plotted on the Y-axis, while the quantity of training templates is shown on the X-axis.

4. CONCLUSION

True acceptance and rejection rates of false positives and false negatives are demonstrated using several popular face recognition datasets. Those models are based on the features of famous people, such as their eyes, noses, and jawlines. The invariant techniques for features that are both angle-and location-invariant and the branch-and-bound feature selection strategy stand out.

In order to assess the method's efficacy, various inputs were used, including images with a resolution of 256 pixels by 256 pixels. When compared to the Feature Based Multimodal Face Recognition System, the MFRS has a lower FAR of 1.05% and a lower FRR of 1.25%. There will be a decrease in effort needed towards the conclusion.

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