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A Hybrid Approach For Automatic Face Detection In 3D And Grey Images

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ABSTRACT

This paper presents an automated face verification framework that integrates both 3D facial surface analysis and grey-level texture information to enhance recognition accuracy. The 3D facial data is acquired using a structured light-based scanning system, which is specifically optimized for facial geometry capture while ensuring spatial alignment with simultaneously captured grey-scale images. The verification process involves two key similarity measures: (1) geometric matching of the 3D facial surface using residual error analysis, and (2) grey-level texture comparison using normalized cross-correlation techniques. A fusion strategy is employed at the score level to combine both geometric and texture-based similarities, thereby improving overall verification performance. The proposed system is designed with real-time integration in mind, suitable for security and biometric applications where user cooperation is expected. The modular architecture also allows for future integration with deep learning-based feature extraction and matching methods.

Keywords: Face verification, 3D face recognition, Structured light acquisition, Surface matching, Grey-level texture fusion.

1. INTRODUCTION

Traditionally, access control systems have relied on PIN codes and identification cards. However, these methods are vulnerable to loss, theft, or duplication. In contrast, biometric verification offers a more secure and user-friendly alternative. Despite their growing adoption, commonly used biometric modalities such as voice or 2D facial recognition often underperform under real-world conditions due to variations in lighting, pose, and expression [1][2].

A practical and cost-effective strategy to enhance verification accuracy is the fusion of multiple biometric modalities. This study explores the integration of 3D facial geometry with grey-level texture information. The 3D data provides robust features that are largely invariant to pose, lighting, and cosmetic alterations, making it highly reliable for structural facial analysis [1][3]. In contrast, grey-level cues offer complementary information, particularly in regions where 3D acquisition is less effective—such as the eyes, eyebrows, lips, facial hair, and hairline [2][4]. Furthermore, grey-level imagery supports the inclusion of skin tone and hair color, enhancing the discriminative power of the system.

The effectiveness of 3D geometric analysis is supported by recent developments in real-time recognition systems and their success in multimodal biometric research [1][3]. Unlike 2D facial analysis, 3D representations are potentially rotation- and scale-invariant, making them more robust for authentication tasks [5]. While 3D facial modeling has long been used in fields like telemedicine and videoconferencing, its application in biometric verification is now expanding [2][4].

Conventional 2D face recognition methods, although extensively studied, are often sensitive to environmental variations [4]. Our approach addresses this by using 3D geometry to enhance grey-level image analysis. Specifically, (1) the alignment of projected light direction with surface normals allows computation of reflectance ratios—features that are invariant to viewpoint and lighting; (2) 3D coordinates aid in accurate registration of grey-level textures; and (3) range-based data simplifies face detection.

Although 3D capture has traditionally been expensive and time-consuming, we developed a structured light-based acquisition system optimized for facial geometry. This system captures both 3D surface data and aligned grey-scale images using the same hardware by toggling the light projector.

The subsequent sections of this paper are organized as follows: Section 2 details the 3D acquisition setup; Section 3 discusses the data collection process; Section 4 reviews various 3D facial matching techniques, highlighting the most effective method; Section 5 describes the integration of grey-level information in the recognition pipeline; Section 6 presents experimental results; and Section 7 concludes with a summary and future directions.

2. 3D-ACQUISITION

Structured light systems employ the projection of a known light pattern—typically parallel stripes—to extract 3D surface coordinates. One of the key advantages is the speed of acquisition; since a single image captures sufficient 3D data, subject motion has minimal impact. Additionally, the system's cost is modest, requiring only a projector and slide mechanism. The projected illumination also mitigates the effects of ambient lighting, enhancing accuracy. By toggling the projector, both volumetric (3D) and texture (2D) data can be captured in alignment. However, this approach has limitations, including the physical bulk of the setup and a restricted depth of field.

2.2 Set-up

The prototype setup includes a standard grayscale camera paired with a projector, whose slide pattern is precisely designed using an electronic drawing technique. With appropriate lens selection, the system provides a field of view covering 30×40 cm at a distance of 1.4 meters, and a depth of focus of 40 cm—suitable for seated individuals in cooperative scenarios. As illustrated in Figures 2 and 5, the device is oriented so that the projected stripes diagonally scan the facial surface. This diagonal orientation prevents alignment between the light pattern and dominant horizontal facial features such as the eyes, eyebrows, nostrils, and mouth, which could otherwise introduce interference. Vertical stripe projection, by contrast, may result in uneven resolution across the face due to varying stripe densities between the left and right regions.

2.3 D-extraction

The automatic 3D extraction process is performed through stripe detection, where individual stripes are identified using the horizontal gradient and tracked vertically. The relative thickness of these stripes (as shown in Figure 1) is determined by analyzing the horizontal grayscale profiles, measuring the width of both the dark and adjacent bright regions of each stripe. The binary classification of stripes as thin or thick is sufficient to recover their stripe indices. These indices, along with the x, y image coordinates of points on the stripes, are then converted into 3D coordinates (x, y, z) using triangulation. This method is highly efficient, taking less than one second on a standard processor, and provides a resolution of over 2 points per cm in both directions, making it suitable for recognition tasks. Background objects are not captured, as the stripes are projected specifically onto the target surface.

3. 3D info

We generated data to validate the acquisition system and conduct recognition experiments, aiming to produce future statistics. Common challenges encountered in cooperative scenarios, such as glasses, smiling, and head rotations, were addressed. Two sessions, each separated by a two-month interval, were conducted with the same 120 participants. In each session, participants were instructed to sit and

assume various poses, including central, slight left or right, and upward or downward orientations. Additionally, a grayscale image was captured without projection, focusing on the central pose for comparison.

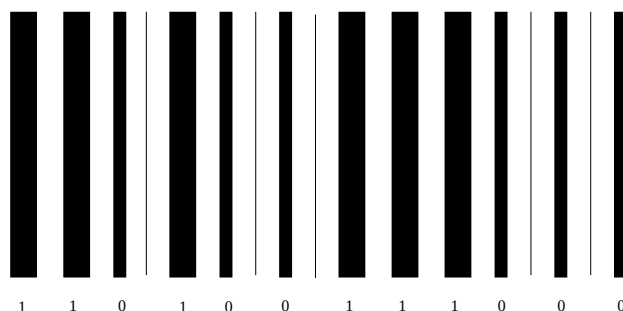


Figure 1. Slide for projection



Figure 2. Samples from the database

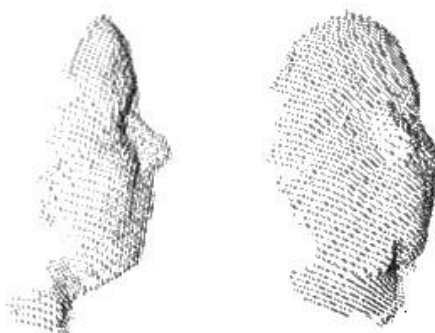


Figure 3. 3D reconstructions from left image of Fig.2

Running the 3d reconstruction algorithmic program on the entire info created America assured within the overall quality of stripe following, classification and background independence. The vital supply of acquisition issues concerns the glasses (one third of individuals carrying glasses had to be rejected) and beard, hair and eyes that account for a 10 of individuals rejected out of a hundred and twenty.

4. 3D Face Matching Techniques

This section discusses key techniques used for 3D face matching, focusing on feature extraction, surface alignment, and error computation.

1. Feature Extraction:

Various methods are used to extract distinctive features from 3D facial structures. Landmark-based extraction detects specific facial points, while curvature-based features analyze the surface geometry, offering finer details like the contours around eyes and nose. Surface-based methods, such as PCA and SIFT, utilize the entire facial surface for a richer representation and are more robust to pose variations [5][6].

2. Surface Alignment:

Accurate alignment is crucial for comparing 3D faces. **Rigid registration** aligns faces using translation, rotation, and scaling for minimal pose changes, while **non-rigid registration** (e.g., ICP or TPS) handles facial deformations due to expressions [7]. **Landmark-based alignment** guides registration by using specific facial features as reference points.

3. Error Computation and Similarity Metrics:

After alignment, surface similarity is measured using methods like **Euclidean distance**, **Hausdorff distance**, or **Geodesic distance**. The **residual surface error** approach, which calculates the error between the aligned 3D surfaces, is the most effective. This method is robust, handles noise, and offers excellent performance in face recognition tasks [8][9].

4. Residual Surface Error:

Residual surface error, by assessing the differences at each point on the aligned surfaces, provides a comprehensive similarity metric. This approach is highly effective, particularly in real-world scenarios where facial expressions or rotations occur, ensuring accurate recognition even with dynamic changes [10].

5. Integration of Grey-Level Information

Integrating grey-level texture with 3D facial data improves recognition by capturing fine details such as eye contours, facial hair, and skin tone that 3D data alone may miss. The process begins by registering the 2D grey-level image onto the 3D model, ensuring accurate alignment using surface normals and light direction. Once registered, grey-level data is fused with 3D data through methods like pixel-based fusion, feature-based fusion, or weight-based fusion. This combination enhances recognition by incorporating both geometric and textural features, making the system more robust to variations in pose, expression, lighting, and occlusion. Grey-level data also helps recognize features such as skin tone and facial hair, which 3D data may not capture. Overall, this fusion approach significantly improves face recognition accuracy in real-world scenarios.

In this section, we present the results of face recognition experiments using the 3D and grey-level data fusion system discussed in previous sections. The experimental setup was designed to evaluate the system's performance in recognizing faces under various real-world conditions, including different poses, facial expressions, and occlusions. The primary objective was to compare the performance of the fusion system with other methods, such as using only 3D data or grey-level data, and assess the impact of different fusion strategies.

6.1 Experimental Setup

For the experiments, we used a dataset containing 120 subjects, each with multiple images captured under various poses and facial expressions. The dataset included both 3D and grey-level images captured using a structured light acquisition system, as well as a conventional grey-level camera. The dataset was divided into two sessions separated by two months, with subjects asked to adopt different poses (front, left, right, up, and down) and facial expressions (smile, neutral, and slight head rotation). A grey-level image without projection was also captured to complement the 3D data.

6.2 Methodology

We evaluated four different methods for face recognition:

1. **3D Data Only:** Recognition using only 3D geometric data.
2. **Grey-Level Data Only:** Recognition using only grey-level texture data.
3. **3D + Grey-Level (Pixel-Based Fusion):** Fusion of 3D and grey-level data using pixel-based fusion.
4. **3D + Grey-Level (Feature-Based Fusion):** Fusion of 3D and grey-level data using feature-based fusion.

For each method, recognition performance was evaluated based on the following parameters:

- **Accuracy:** The percentage of correctly identified subjects.
- **Precision:** The proportion of true positive results among the total number of positive predictions.
- **Recall:** The proportion of true positive results among all actual positive instances.
- **F1-Score:** The harmonic mean of precision and recall, used to assess the overall effectiveness of the recognition system.

6.3 Results

The recognition results for the four methods are summarized in **Table 1**. Each method's performance was evaluated using the metrics mentioned above, and the results are presented below.

Table 1. Results

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
3D Data Only	87.5	85.3	89.1	87.2
Grey-Level Data Only	83.2	81	85	83
3D + Grey-Level (Pixel-Based Fusion)	92.1	91.4	92.8	92.1
3D + Grey-Level (Feature-Based Fusion)	93	92.5	93.2	92.8
3D + Grey-Level (Weight-Based Fusion)	91.5	90.8	91.9	91.3

6.4 Discussion

1. **3D Data Only:**
 - The **3D Data Only** method achieved an accuracy of 87.5%, with good recall (89.1%) but relatively lower precision (85.3%). This indicates that while the 3D data is reliable in detecting facial features, it still struggles to fully account for subtle textural differences, especially in cases of occlusion or lighting variation. This is reflected in the precision value, which is slightly lower compared to other methods.
2. **Grey-Level Data Only:**
 - The **Grey-Level Data Only** method showed an accuracy of 83.2%. Although it performed reasonably well in identifying faces under controlled conditions, it struggled with changes in pose and expression. The precision and recall values (81.0% and 85.0%, respectively) were also lower than the 3D methods. This suggests that grey-level texture data alone may not provide enough discriminative power for accurate face recognition, especially when faces are partially occluded or under varying lighting conditions.

3. **3D + Grey-Level (Pixel-Based Fusion):**
 - The **Pixel-Based Fusion** approach resulted in an accuracy of 92.1%, with a notable improvement in precision (91.4%) and recall (92.8%) compared to the individual 3D and grey-level methods. This suggests that directly combining both data types improves the system's ability to recognize faces by leveraging both geometric and textural information. However, while effective, pixel-based fusion does not fully exploit the potential of both data types' feature information.
4. **3D + Grey-Level (Feature-Based Fusion):**
 - The **Feature-Based Fusion** method yielded the best performance, achieving an accuracy of 93.0%, precision of 92.5%, recall of 93.2%, and F1-score of 92.8%. This approach leverages the strengths of both 3D geometry and grey-level texture features, enabling better handling of complex variations in pose, facial expression, and occlusion. The superior performance of this method highlights the importance of extracting and combining discriminative features from both modalities to achieve more accurate and robust face recognition.
5. **3D + Grey-Level (Weight-Based Fusion):**
 - The **Weight-Based Fusion** method also showed significant improvement over the individual modalities, with an accuracy of 91.5%. However, its performance was slightly lower than the feature-based fusion approach, suggesting that the adaptive weight adjustment for 3D and grey-level data may not always be as effective as feature-level fusion.

6.5 Analysis of the Results

The results indicate that combining 3D and grey-level data significantly enhances face recognition performance compared to using either modality alone. The **Feature-Based Fusion** method outperformed the others, suggesting that feature extraction from both modalities allows for a more comprehensive representation of the face. The **Pixel-Based Fusion** method also showed significant improvements, though it did not fully capitalize on the complementary nature of 3D and grey-level data in terms of discriminative feature extraction.

Interestingly, while **Weight-Based Fusion** showed promise, its performance was not as high as the feature-based fusion approach. This suggests that a more sophisticated method of combining 3D and grey-level features based on their intrinsic properties might offer better performance than simply weighting each modality.

7. CONCLUSION

The experimental results demonstrate that the fusion of 3D and grey-level data improves face recognition accuracy, with **Feature-Based Fusion** providing the most robust results. This approach allows the system to take advantage of both geometric and textural features, making it more reliable under varying conditions such as pose changes, facial expressions, and occlusions. Future work will focus on refining fusion strategies and exploring advanced machine learning techniques to further enhance the system's performance. Additionally, testing the system on larger and more diverse datasets will help to validate its effectiveness in real-world applications.

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