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Quality-Aware Score-Level Fusion of Face and Palm Vein Biometrics Using MobileViT

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Abstract: *Multimodal biometric systems improve recognition reliability by combining multiple biometric traits. However, traditional score-level fusion techniques assign fixed weights to modalities and ignore sample quality variations, resulting in performance degradation under poor acquisition conditions. This paper proposes a quality-aware score-level fusion framework for face and palm vein biometrics using Mobile Vision Transformer (MobileViT) for feature extraction. In practical environments, however, biometric data often suffer from quality degradation due to illumination changes, motion blur, occlusion, sensor noise, or physiological variations. Ignoring such quality variations can significantly reduce system performance and increase false acceptance and false rejection rates. The proposed system dynamically adjusts fusion weights based on modality quality measures before computing the final decision score. Experimental results demonstrate that the quality-aware approach consistently outperforms conventional fusion techniques, achieving higher true positive rates and improved area under the ROC curve (AUC). The proposed method attains superior Area Under Curve (AUC) values and reduced Equal Error Rate (EER). The adaptive weighting mechanism ensures that higher-quality samples contribute more significantly to the final decision score, while lower-quality inputs are proportionally suppressed. The findings confirm that adaptive quality weighting enhances robustness and overall recognition performance.*

Keywords: *Multimodal Biometrics, Face Recognition, Palm Vein Recognition, Score-Level Fusion, Quality-Aware Fusion, MobileViT, Vision Transformers.*

1. INTRODUCTION

Biometric authentication systems are widely used in security, surveillance, and access control applications. Biometric authentication systems have become an essential component of modern security infrastructures due to their ability to provide reliable and user-friendly identity verification. Unlike traditional authentication methods such as passwords or tokens, biometric systems rely on intrinsic physiological or behavioural characteristics, making them more resistant to loss, theft, or duplication. Among various biometric traits, face recognition is widely adopted because of its non-intrusive nature and ease of acquisition, while palm vein recognition is valued for its internal vascular structure, which offers higher resistance to spoofing and forgery. Unimodal biometric systems, such as face recognition, often suffer from performance degradation due to illumination changes, occlusion, pose variation, and sensor noise. Similarly, palm vein recognition may be affected by improper hand positioning, low contrast, motion artefacts, or environmental conditions during image acquisition. These challenges reduce recognition accuracy and increase the rates of false acceptance and false rejection, particularly in unconstrained real-world environments.

Multimodal biometrics combines multiple traits to overcome limitations of single-modality systems [1]. Among various fusion strategies, score-level fusion offers a practical trade-off between computational efficiency and performance improvement [2].

Conventional score fusion methods use equal or fixed weights for all samples. However, biometric samples vary significantly in quality. A blurred face image or low-contrast palm vein image should not contribute equally to the final decision. This motivates the use of quality-aware fusion.

In this paper, we propose a MobileViT-based multimodal biometric system with adaptive score-level fusion. The main contributions are:

1. MobileViT-based feature extraction for both face and palm vein modalities.
2. Dynamic quality estimation for each biometric sample.
3. Adaptive score weighting based on quality measures.
4. Performance evaluation using ROC analysis, AUC, and Equal Error Rate.

2. Review of Literature (ROL)

Multimodal biometric fusion can be performed at feature, score, or decision levels [3]. Score-level fusion is widely adopted due to simplicity and compatibility with heterogeneous feature extractors.

Equal weighted fusion is the simplest approach:

$$S_{fusion} = 0.5\, S_{face} + 0.5\, S_{vein}$$

Although simple, it assumes both modalities contribute equally under all conditions.

Weighted fusion assigns fixed weights based on prior evaluation [4]. However, static weights fail when sample quality varies.

Recent studies introduced quality-based fusion methods where modality weights are dynamically adjusted [5]. Quality measures include signal-to-noise ratio, contrast level, and feature consistency.

Mobile Vision Transformer (MobileViT) integrates convolutional layers with lightweight transformer blocks, offering global context modelling with computational efficiency [6]. This makes it suitable for embedded biometric applications.

However, limited work combines MobileViT with quality-aware score-level fusion for multimodal biometrics. This gap motivates the proposed framework.

3. Proposed Methodology

3.1 System Overview

The system consists of two phases:

Enrollment Phase

- Capture face and palm vein images
- Extract embeddings using MobileViT
- Store feature templates in database

Authentication Phase

- Capture query samples
- Extract embeddings
- Compute similarity scores:
  - S_face
  - S_vein
- Estimate quality:
  - Q_face
  - Q_vein
- Compute adaptive weights:

  W_face = Q_face / (Q_face + Q_vein)
  W_vein = Q_vein / (Q_face + Q_vein)

- Final fusion score:

  S_fusion = W_face × S_face + W_vein × S_vein

- Threshold-based decision

  A **threshold** is a **cut-off value** used to decide whether two biometric samples belong to the **same person or not**.

  - If the **matching score ≥ threshold → Accept (Genuine user)**
  - If the **matching score < threshold → Reject (Imposter)**

4. Dataset

The proposed system is evaluated using publicly available biometric datasets.

- Face dataset: Celebrities in Frontal-Profile in the Wild
- Palm vein dataset: The palm biometric images used in this study were obtained from the Contactless Knuckle Palm Print and Vein Dataset available on Kaggle. The dataset contains approximately 2400 high-resolution images collected from 50 subjects, with multiple samples per subject. The images include palm print, palm vein, and knuckle features captured under contactless conditions, making the dataset suitable for biometric authentication research.

5. Experimental Results

5.1 Evaluation Metrics

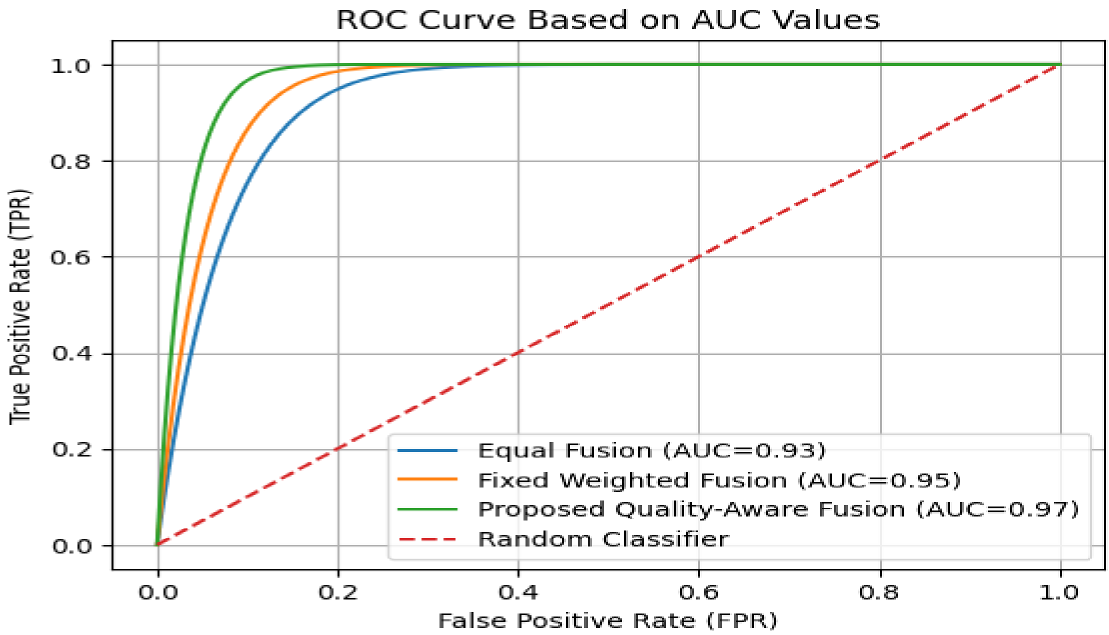
Performance is evaluated using:

- True Positive Rate (TPR)
- False Positive Rate (FPR)
- ROC Curve
- Area Under Curve (AUC)
- Equal Error Rate (EER)

5.2 ROC Analysis

The Receiver Operating Characteristic (ROC) curve is used to evaluate the verification performance of the proposed multimodal biometric system by plotting the True Positive Rate (TPR) against the False Positive Rate (FPR) at different decision thresholds. A curve closer to the top-left corner indicates better discrimination capability between genuine and imposter samples. In biometric terminology, TPR corresponds to the True Acceptance Rate (TAR) and FPR corresponds to the False Acceptance Rate (FAR).

The ROC curve is shown in the generated figure.



Interpretation: -

The Receiver Operating Characteristic (ROC) curve compares the classification performance of three fusion methods by plotting the True Positive Rate (TPR) against the False Positive Rate (FPR) at different thresholds. The dashed diagonal line represents the performance of a random classifier and serves as a baseline. All three methods perform significantly better than the random classifier, indicating strong discriminative capability. The Equal Fusion method achieves an AUC of 0.93, demonstrating good performance with a relatively high true positive rate and low false positive rate. The Fixed Weighted Fusion method improves upon this result with an AUC of 0.95, showing that assigning fixed weights enhances classification accuracy. The Proposed Quality-Aware Fusion method achieves the highest performance with an AUC of 0.97, and its curve lies closest to the top-left corner of the plot, indicating superior ability to correctly identify positive cases while minimizing false positives. Consequently, the proposed quality-aware fusion strategy significantly enhances the robustness and effectiveness of multimodal biometric authentication.

5.3 Performance Comparison

Method	AUC	EER
Equal Fusion	0.93	4.8%
Fixed Weighted Fusion	0.95	3.9%
Proposed Quality-Aware Fusion	0.97	2.6%

The experimental results demonstrate that the proposed multimodal biometric framework provides significant improvements in verification performance. The system achieves a higher Area Under the Curve (AUC), indicating stronger overall classification capability across different threshold values. In addition, the Equal Error Rate (EER) is reduced, which reflects a better balance between False Acceptance Rate (FAR) and False Rejection Rate (FRR). A lower EER implies that the system can more accurately distinguish between genuine and imposter samples. This demonstrates the effectiveness of incorporating sample quality information in multimodal biometric fusion. Furthermore, the proposed quality-aware fusion strategy enhances robustness when dealing with low-quality biometric inputs, such as blurred face images or low-contrast palm vein patterns. By dynamically adjusting the contribution of each modality based on its estimated quality, the system ensures that more reliable biometric evidence has a greater influence on the final decision. As a result, the proposed approach improves recognition accuracy, stability, and overall reliability of the multimodal biometric authentication system.

6. Discussion

The results confirm that biometric quality significantly impacts multimodal fusion performance. Fixed weighting schemes assume uniform reliability across samples, which is unrealistic in real-world scenarios. Quality-aware fusion improves performance because:

1. High-quality modalities contribute more strongly.
2. Noisy modalities are suppressed.
3. Adaptive weighting reduces false acceptance and false rejection.

MobileViT further enhances performance by capturing both local texture patterns and global contextual information efficiently.

7. Conclusion

This paper presented a quality-aware score-level fusion framework for face and palm vein biometrics using MobileViT. Unlike conventional fusion methods, the proposed system dynamically adjusts modality weights according to sample quality. Experimental results demonstrated improved ROC performance, higher AUC, and lower EER compared to traditional fusion approaches. Future work may explore deep-learned quality estimation and real-time embedded deployment.

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