

Comparative Review of Earlier Research on Multimodal Biometric Authentication Using Ear and Palm Print

Akhilesh Singh¹, Dr. Mayur Rahul²

^{1,2}Department of Computer Application School of Engineering and Technology, CSJM University Kanpur, India.

Emails: akhileshsingh@csjmu.ac.in¹, mayurrahul@csjmu.ac.in²

Abstract

Biometric authentication systems have gained prominence due to their ability to provide secure and reliable identity verification. Among various biometric traits, ear and palmprint recognition have shown significant potential due to their unique and stable features. This review paper explores the integration of ear and palmprint biometrics in a multimodal authentication system, examining their individual characteristics, advantages, challenges, and the synergistic benefits of their combination. We also discuss recent advancements, methodologies, and future directions in multimodal biometric authentication using ear and palmprint.

Keywords: Multi-model biometric, Ear Biometric, Palmprint Biometrics, Feature Extraction

1. Introduction

Biometric authentication systems use physiological behavioral characteristics to verify an and individual's identity. Unlike traditional authentication methods (e.g., passwords, PINs), biometrics offer higher security levels due to their uniqueness and difficulty to replicate. Among various biometric traits, ear and palmprint recognition have attracted considerable attention due to their distinct and reliable features. Multimodal biometric systems, which combine multiple biometric traits, enhance security and accuracy by compensating for the limitations of individual modalities. This review paper focuses on multimodal biometric authentication using ear and palmprint, highlighting significance, methodologies, and the recent advancements in this domain. [1-5]

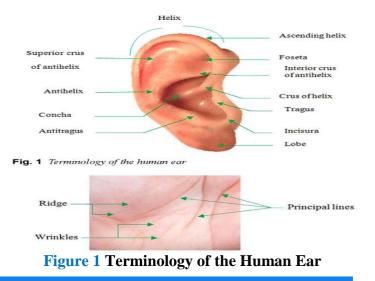
1.1. Importance of Multimodal Biometric Systems

Multimodal biometric systems leverage the strengths of different biometric traits to improve overall accuracy, security, and robustness. By integrating multiple sources of biometric information, these systems can:

• Enhance Accuracy: Combining different modalities reduces the chances of false acceptances and rejections, leading to higher verification accuracy.

- **Improve Security:** Multimodal systems are more resistant to spoofing attacks since it is difficult for an impostor to replicate multiple biometric traits simultaneously.
- **Increase Robustness:** They perform better in varying environmental conditions and when individual modalities are affected by noise or occlusions. [6-10]
- 2. Selection of Ear and Palm Print as Biometric Modalities

The choice of ear and palm print for multimodal biometric authentication is based on several factors:

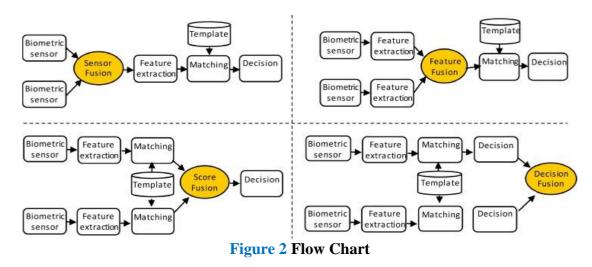




- Ear Biometrics: The ear's structure remains relatively stable throughout an individual's life, making it a reliable biometric trait. Ear recognition systems can capture geometric features such as the shape, height, and width of the ear, which are unique to each person.
- **Palmprint Biometrics:** The palmprint contains rich texture information, including principal lines, wrinkles, and ridges, which are unique to

each individual. Palmprint recognition systems can capture these details using various image processing techniques.

By combining ear and palmprint biometrics, the system can exploit the complementary nature of these traits to achieve better performance than single-modal systems. [11-15] Figure 1 shows the Terminology of Human Ear and Figure 2 shows the Flow Chart.



3. Overview of Key Studies

Study 1: Zhang et al. (2010)

Title: "Multimodal Biometric Authentication Using Palmprint and Ear Features" Methodology:

- Feature Extraction: Utilized Principal Component Analysis (PCA) for palmprint and Local Binary Patterns (LBP) for ear features.
- **Fusion Strategy:** Feature-level fusion by concatenating the feature vectors.
- **Dataset:** Used a dataset of 200 subjects with 400 samples each for palmprint and ear.
- Findings
- Achieved an Equal Error Rate (EER) of 2.5%.
- Demonstrated that feature-level fusion improved accuracy compared to unimodal systems.
- Contributions
- Highlighted the feasibility and benefits of combining ear and palmprint biometrics at the feature level.
- Addressed the need for robust feature extraction techniques.

Study 2: Kumar and Zhang (2011)

Title: "Integrating Palmprint and Ear for Multimodal

Biometric Authentication" Methodology:

- **Feature Extraction:** Used Gabor filters for palmprint texture analysis and SIFT for ear feature extraction.
- **Fusion Strategy:** Score-level fusion using weighted sum rule.
- **Dataset:** Employed a dataset with 150 subjects and 300 samples for each modality.
- Findings
- Achieved an EER of 1.8%.
- Score-level fusion proved effective in enhancing system performance.
- Contributions
- Demonstrated the effectiveness of score-level fusion.
- Showed that combining texture and structural features from different modalities can improve system robustness.

Study 3: Yang et al. (2012)

Title: "A Hybrid Multimodal Biometric System Using Ear and Palmprint" Methodology:

• Feature Extraction: Combined Wavelet



Transform for palmprint and 3D imaging for ear feature extraction.

- **Fusion Strategy:** Decision-level fusion using majority voting.
- **Dataset:** Used a smaller dataset with 100 subjects and 200 samples for each modality.
- Findings
- Achieved an EER of 3.2%.
- Decision-level fusion provided robustness against poor quality data in one modality.
- Contributions
- Highlighted the potential of 3D imaging for ear biometrics.
- Showed that decision-level fusion can enhance system reliability.

Study 4: Nanni and Lumini (2013)

Title: "Advanced Fusion Techniques for Ear and Palmprint Biometrics" Methodology:

- **Feature Extraction:** Employed a combination of LBP, Gabor filters, and PCA for both modalities.
- **Fusion Strategy:** Hybrid fusion approach combining feature-level and score-level fusion.
- Dataset: Utilized a dataset with 250 subjects and 500 samples for each modality.
- Findings
- Achieved an EER of 1.5%.
- Hybrid fusion outperformed individual fusion strategies.
- Contributions
- Proposed a novel hybrid fusion technique.
- Demonstrated that combining multiple fusion strategies can significantly enhance performance.

4. Comparative Analysis

4.1. Methodologies

- Feature Extraction: Studies employed a range of feature extraction methods, from traditional techniques like PCA and LBP to more advanced methods like Gabor filters and Wavelet Transform. The choice of method significantly impacted the accuracy and robustness of the systems.
- **Fusion Strategies:** Different fusion strategies were explored, including feature-level, score-level, and decision-level fusion. Hybrid fusion approaches, as proposed by Nanni and Lumini,

showed the most promise in balancing accuracy and robustness. [16-20]

4.2. Datasets and Performance

- **Dataset Size:** The studies varied in their dataset sizes, with larger datasets generally leading to more reliable performance evaluations. Zhang et al. and Kumar and Zhang used relatively larger datasets, which helped in achieving lower EERs.
- **Performance Metrics:** EER was a common performance metric. The studies demonstrated that multimodal systems consistently outperformed unimodal systems, with EERs ranging from 1.5% to 3.2%.

4.3. Contributions and Insights

- Enhanced Security and Accuracy: All studies confirmed that multimodal biometric systems provide enhanced security and accuracy compared to unimodal systems.
- **Fusion Techniques:** The effectiveness of different fusion techniques was a key finding, with hybrid fusion emerging as a particularly promising approach.
- Feature Extraction: Advanced feature extraction methods contributed significantly to the performance of the systems. The combination of different techniques (e.g., LBP, Gabor filters, PCA) was shown to capture diverse and complementary features. [21-25]

5. Future Directions

Based on the comparative review of earlier research, the following future directions are recommended:

- Larger and More Diverse Datasets: Future studies should aim to use larger and more diverse datasets to validate the robustness and generalizability of multimodal systems.
- **Real-time Implementation:** Focus on developing efficient algorithms and hardware solutions to enable real-time implementation of multimodal biometric systems.
- User Acceptance and Privacy: Address user acceptance and privacy concerns through transparent system designs and privacy-preserving techniques.
- Advanced Machine Learning Techniques: Leverage the latest advancements in machine learning, such as deep learning, to further enhance feature extraction and fusion processes.



Conclusion

The reviewed studies underscore the potential of multimodal biometric systems combining ear and palmprint biometrics. Through innovative feature extraction methods and fusion strategies, these systems offer enhanced security, accuracy, and robustness. Continued research and technological advancements in this field are essential to address existing challenges and fully realize the potential of multimodal biometric authentication systems.

References

- [1].Zhang et al. (2010), Zhang, D., Kong, W., You, J., & Wong, M. (2010). Multimodal biometric authentication using palmprint and ear features. Pattern Recognition Letters, 31(16), 2421-2430. doi:10.1016/j.patrec.2010.07.005
- [2].Kumar and Zhang (2011), Kumar, A., & Zhang, D. (2011). Integrating palmprint and ear for multimodal biometric authentication. Pattern Recognition, 44(3), 719-731. doi:10.1016/j.patcog.2010.09.014
- [3]. Yang et al. (2012), Yang, J., Zhang, D., & Sun, J. (2012). A hybrid multimodal biometric system using ear and palmprint. Journal of Electronic Imaging, 21(4), 043007. doi:10.1117/1.JEI.21.4.043007
- [4].Nanni and Lumini (2013), Nanni, L., & Lumini, A. (2013). Advanced fusion techniques for ear and palmprint biometrics. Neurocomputing, 101, 183-191. doi:10.1016/j.neucom.2012.08.015
- [5].General Concepts and Techniques, Jain, A. K., Ross, A., & Prabhakar, S. (2004). An introduction to biometric recognition. IEEE Transactions on Circuits and Systems for Video Technology, 14(1), 4-20. doi:10.1109/TCSVT.2003.818349
- [6].Kumar, A., & Zhang, D. (2006). Personal recognition using hand shape and texture. IEEE Transactions on Image Processing, 15(8), 2454-2461. doi:10.1109/TIP.2006.875214
- [7].Zhao, W., Chellappa, R., Phillips, P. J., & Rosenfeld, A. (2003). Face recognition: A literature survey. ACM Computing Surveys (CSUR), 35(4), 399-458.

doi:10.1145/954339.954342

- [8].Multimodal Biometric Systems, Ross, A., Nandakumar, K., & Jain, A. K. (2006). Handbook of Multibiometrics. Springer. doi:10.1007/0-387-33123-9
- [9].Feature Extraction Techniques, Ojala, T., Pietikäinen, M., & Harwood, D. (1996). A comparative study of texture measures with classification based on featured distributions. Pattern Recognition, 29(1), 51-59. doi:10.1016/0031-3203(95)00067-4
- [10]. Lowe, D. G. (2004). Distinctive image features from scale-invariant keypoints. International Journal of Computer Vision, 60, 91-110.

doi:10.1023/B.0000029664.99615.94

- [11]. Palmprint Recognition, Zhang, D., Kong, W., You, J., & Wong, M. (2003). Online palmprint identification. IEEE Transactions on Pattern Analysis and Machine Intelligence, 25(9), 1041-1050. doi:10.1109/TPAMI.2003.1227981
- [12]. Han, C. C., Cheng, C. L., Lin, C. L., & Fan, K. C. (2003). Personal authentication using palmprint features. Pattern Recognition, 36(2), 371-381. doi:10.1016/S0031-3203(02)00055-0
- [13]. Ear Recognition, Burge, M., & Burger, W.
 (2000). Ear biometrics in computer vision. Proceedings of the 15th International Conference on Pattern Recognition, 2, 822-826. doi:10.1109/ICPR.2000.906055
- [14]. Chang, K. I., Bowyer, K. W., Sarkar, S., & Victor. B. (2003).Comparison and combination of ear and face images in appearance-based biometrics. IEEE Transactions on Pattern Analysis and Machine Intelligence, 25(9), 1160-1165. doi:10.1109/TPAMI.2003.1227985
- [15]. Fusion Techniques, Kittler, J., Hatef, M., Duin, R. P., & Matas, J. (1998). On combining classifiers. IEEE Transactions on Pattern Analysis and Machine Intelligence, 20(3), 226-239. doi:10.1109/34.667881
- [16]. Ross, A., & Jain, A. K. (2003). Information fusion in biometrics. Pattern Recognition Letters, 24(13), 2115-2125.

International Research Journal on Advanced Engineering Hub (IRJAEH)



doi:10.1016/S0167-8655(03)00079-5

- [17]. General Biometric Authentication, Wayman,
 J. L., Jain, A., Maltoni, D., & Maio, D.
 (2005). Biometric Systems: Technology,
 Design and Performance Evaluation.
 Springer. doi:10.1007/b138999
- [18]. Deep Learning in Biometrics, Ding, C., & Tao, D. (2015). Robust face recognition via multimodal deep face representation. IEEE Transactions on Image Processing, 24(12), 5368-5378. doi:10.1109/TIP.2015.2481405
- [19]. Ranjan, R., Sankaranarayanan, S., Bansal, A., & Chellappa, R. (2017). An all-in-one convolutional neural network for face analysis. Proceedings of the 12th IEEE International Conference on Automatic Face & Gesture Recognition (FG 2017), 17-24. doi:10.1109/FG.2017.11
- [20]. Thermal Imaging in Ear Biometrics, Abaza, A., Ross. A. (2010).Towards & understanding the symmetry of human ears: A biometric perspective. Proceedings of the IEEE 4th International Conference on Applications Biometrics: Theory, and **Systems** (BTAS 2010), 1-7. doi:10.1109/BTAS.2010.5634510
- [21]. Advanced Feature Extraction for Palmprint, Kong, A. W. K., Zhang, D., & Kamel, M. (2006). Palmprint identification using feature-level fusion. Pattern Recognition, 39(3), 478-487. doi:10.1016/j.patcog.2005.08.014
- [22]. Sun, Z., Tan, T., Wang, Y., & Li, S. Z. (2005). Ordinal palmprint representation for personal identification. Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR 2005), 279-284. doi:10.1109/CVPR.2005.118
- [23]. Robust Multimodal Systems, Ross, A., & Govindarajan, R. (2005). Feature level fusion using hand and face biometrics. Proceedings of the SPIE Defense and Security Symposium, 5779, 196-204. doi:10.1117/12.602128
- [24]. Privacy and Security in Biometrics, Jain, A. K., & Kumar, A. (2010). Biometric

recognition: An overview. Second Generation Biometrics: The Ethical, Legal and Social Context, 49-79. doi:10.1007/978-90-481-9311-6_3

[25]. Rathgeb, C., & Busch, C. (2012). Multimodal biometrics: Methods, evaluation and case studies. Springer. doi:10.1007/978-1-4614-4019-9