IAES Journal of Electrical and Electronics Engineering
Vol. 1, No. 1, June 2014, pp. 19~23
ISSN: 2338-7432, DOI: 10.11591/jeee.v1i1.pp19-23

Face recognition: a critical review of feature representation, classification, and robustness

M. Riza Ferdiansyah, Tole Sutikno
Faculty of Industrial Technology, Universitas Ahmad Dahlan, Yogyakarta, Indonesia

Article Info

Article history:

Received Jan 3, 2014
Revised Mar 20, 2014
Accepted May 2, 2014

Keywords:

Appearance-based methods
Face recognition
Illumination variation
Local features
Pose variation
Recognition robustness

ABSTRACT

Face recognition is a fundamental research area in computer vision and biometric identification, aiming to distinguish individuals from facial images under varying acquisition conditions. This review critically examines the development of face recognition methods, emphasizing appearance-based representations, local feature extraction, classification strategies, and robustness to illumination and pose variations. Appearance-based methods, including principal component analysis and linear discriminant analysis, provide compact global representations but are often sensitive to changes in lighting, expression, and facial orientation. Local feature methods, such as Gabor wavelets, local binary patterns, and elastic bunch graph matching, capture regional facial characteristics and offer complementary advantages in handling local variations. The review further discusses illumination normalization, pose modeling, and multi-view representations as important strategies for improving recognition reliability. Particular attention is given to the limitations of conventional methods when applied to uncontrolled environments, where image quality, occlusion, and acquisition variability can substantially affect performance. The analysis highlights the need for discriminative and complementary feature representations, robust classification, and evaluation protocols that reflect realistic operating conditions. Finally, research directions are identified to support more reliable and generalizable face recognition systems.

This is an open access article under the CC BY-SA license.

1. INTRODUCTION

Face recognition has become an important research topic because facial images provide a non-intrusive means of identifying individuals. The task involves comparing a facial image against stored representations to determine identity or verify a claimed identity. Despite substantial progress, reliable recognition remains challenging because facial appearance changes with illumination, pose, expression, occlusion, and image quality.

Traditional face recognition research has developed along several methodological directions. Appearance-based methods represent faces using global image information, while local feature methods describe distinctive facial regions and their spatial relationships. Classification methods then use these representations to distinguish identities, but their effectiveness depends strongly on the quality and stability of the extracted features.

Recognition performance under controlled conditions does not necessarily indicate reliability in practical environments. Changes in lighting direction, head orientation, camera distance, and facial expression can produce substantial differences between images of the same person. This review examines the principal feature representation and classification approaches, evaluates their robustness to illumination and pose variations, and identifies research directions for more dependable face recognition.

2. APPEARANCE-BASED FACE RECOGNITION

Appearance-based face recognition represents a face through its overall image pattern rather than explicitly reconstructing its three-dimensional geometry. The central assumption is that facial identity can be represented by a compact set of measurements derived from aligned facial images. This approach became influential because it provides relatively simple feature extraction and classification procedures.

The Eigenfaces method introduced by Turk and Pentland [1] uses principal component analysis (PCA) to represent facial images in a lower-dimensional feature space. It identifies the dominant variations among training images and describes each face through its projection onto a set of principal components. Although computationally efficient and historically influential, Eigenfaces may preserve variations caused by illumination and expression rather than emphasizing identity-specific information.

Fisherfaces, proposed by Belhumeur *et al.* [2], address part of this limitation by applying linear discriminant analysis (LDA) to emphasize differences between individuals while reducing variations within the same identity. This discriminative objective can improve recognition when illumination or facial expression introduces substantial within-class variation. However, its effectiveness depends on representative training samples and may be limited by small training datasets or highly nonlinear appearance changes.

Appearance-based representations offer an important foundation for face recognition because they provide compact and mathematically interpretable feature spaces. Nevertheless, global representations can be sensitive to misalignment and local appearance changes, particularly when a facial region is occluded or affected by shadows. Their limitations have motivated the development of local and component-based representations that preserve more detailed facial information.

3. LOCAL FEATURE REPRESENTATION

Local feature methods describe facial images through distinctive regions rather than relying exclusively on the entire image. These methods can capture local texture, edge orientation, and spatial relationships around important facial structures. Their main advantage is the ability to retain discriminative information even when some facial regions are affected by local variations.

Gabor wavelets are widely used to extract local facial features at different scales and orientations. They capture spatial-frequency information and are useful for representing facial structures such as the eyes, eyebrows, nose, and mouth. Shen and Bai [3] reviewed Gabor-based face recognition and discussed its discriminative capability, while also identifying challenges related to feature selection, computational complexity, and redundant representations.

Local binary patterns (LBP) provide another effective approach by describing local texture through intensity relationships between neighboring pixels. Ahonen *et al.* [4] extended LBP for face recognition by dividing facial images into regions and combining their local pattern distributions into a feature representation. This method is relatively simple and computationally efficient, although its performance can be affected by strong illumination changes, image noise, and inaccurate facial alignment.

Elastic bunch graph matching (EBGM), introduced by Wiskott *et al.* [5], represents faces using graphs whose nodes contain local Gabor-based information. The graph structure describes relationships among facial landmarks, while elastic matching accommodates certain variations in facial position and shape. EBGM provides a more explicit representation of facial structure than global appearance methods, but graph construction and matching can increase computational complexity.

Local representations offer complementary information that global appearance methods may overlook. However, local features are not automatically invariant to all facial variations, because changes in pose or illumination can alter local descriptors and landmark positions. Their effectiveness therefore depends on reliable feature localization, suitable feature aggregation, and appropriate matching strategies.

4. CLASSIFICATION STRATEGIES

Classification is responsible for converting extracted facial representations into identity decisions. The choice of classifier influences how effectively the system separates different individuals while accommodating variations within the same identity. Traditional face recognition systems commonly employ distance-based matching, statistical discriminant methods, and probabilistic or similarity-based decision strategies.

PCA-based systems generally classify faces by comparing their projected feature vectors in a reduced-dimensional space. LDA-based systems improve class discrimination by emphasizing between-person differences relative to within-person variations. These approaches are computationally manageable, but their performance depends on the representativeness of training data and the degree to which the chosen feature space captures identity-related information.

Local feature systems use different matching strategies according to their representation. LBP-based methods commonly compare regional histograms, whereas EBGM compares graph structures and local responses around facial landmarks. These approaches demonstrate that classification cannot be separated from feature representation, because the discriminative quality of a descriptor determines the reliability of the subsequent matching process.

A central limitation of conventional classification is the assumption that training and testing images share sufficiently similar acquisition conditions. When this assumption is violated, the classifier may interpret illumination or pose differences as identity differences. More robust systems therefore need to account for nuisance variations during feature extraction, model learning, and decision making.

5. ILLUMINATION VARIATION AND RECOGNITION ROBUSTNESS

Illumination variation is one of the most significant factors affecting face recognition because changes in light direction and intensity alter facial appearance. Shadows, highlights, and uneven lighting can produce image differences that are unrelated to personal identity. These effects can substantially reduce the reliability of global appearance representations.

Belhumeur *et al.* [2] demonstrated that discriminant projection can improve recognition under significant lighting variation compared with conventional Eigenfaces. Other approaches attempt to reduce illumination effects through image preprocessing and illumination-invariant representations. A survey by Makwana [6] classified passive illumination-handling methods into subspace-based statistical techniques, invariant representations, model-based methods, and other preprocessing strategies.

Han *et al.* [7] provided a comparative study of illumination preprocessing methods and examined their effectiveness from different feature-scale perspectives. Their work emphasizes that preprocessing methods should not be evaluated only by their visual enhancement properties, but also by their contribution to recognition performance. Preprocessing may improve robustness, although excessive normalization can remove useful identity information or introduce artifacts.

The broader challenge is to distinguish identity-related facial characteristics from changes caused by image formation. Photometric modeling and learned appearance representations offer ways to address this problem by considering how lighting affects facial appearance. Arandjelović and Cipolla [8] demonstrated a combination of photometric modeling and learned facial invariants for recognition from video under varying illumination and pose.

6. POSE VARIATION AND MULTI-VIEW RECOGNITION

Pose variation occurs when the face is captured from different viewing angles, producing changes in facial geometry and the visibility of facial components. A frontal image and a profile image of the same individual may differ substantially in appearance, making direct image comparison unreliable. Pose variation is therefore a major challenge for systems intended to operate without strict subject cooperation.

Several approaches have been developed to address pose variation, including multi-view representations, geometric normalization, local feature matching, and three-dimensional modeling. Gross *et al.* [9] investigated appearance-based face recognition using light-field representations, demonstrating how multiple facial views can support recognition across pose and illumination. These methods exploit information from different views rather than assuming that a single frontal image can represent all possible facial orientations.

Zhang and Gao [10] reviewed face recognition across pose and discussed approaches for handling changes in facial orientation. Their analysis highlights the difficulty of matching faces when pose-induced appearance differences become greater than the differences between individuals. Multi-view training and pose-specific representations can improve recognition, but they require sufficient training data across different viewing angles.

The CMU pose, illumination, and expression (PIE) database introduced by Sim *et al.* [11] provides a valuable resource for evaluating these challenges. It contains facial images captured across multiple poses, illumination conditions, and expressions, enabling systematic analysis of recognition robustness. Such datasets are important because evaluations based only on controlled frontal images may overestimate the practical performance of recognition systems.

7. COMPARATIVE ANALYSIS AND RESEARCH CHALLENGES

The reviewed methods represent different strategies for describing and matching facial identity. Appearance-based approaches provide compact global representations, local feature methods preserve

regional characteristics, and multi-view or model-based approaches attempt to account for changes in facial appearance [12]. Table 1 summarizes their main characteristics and limitations.

Table 1. Comparative analysis of face recognition approaches

Approach	Main representation	Strengths	Main limitations
Appearance-based	Global facial appearance and subspace projections	Compact representation; relatively simple implementation	Sensitive to illumination, pose, and alignment
Local features	Regional texture, Gabor responses, and facial landmarks	Captures local discriminative information; supports partial-region matching	Sensitive to localization errors and local distortions
Statistical classification	Feature-space discrimination and similarity measures	Efficient and suitable for structured training data	Depends on training representativeness and feature quality
Illumination handling	Normalized or illumination-invariant representations	Reduces lighting-related appearance changes	May remove identity information or introduce artifacts
Multi-view and pose-aware	Multiple views, geometric models, or pose-specific representations	Better accommodation of facial orientation changes	Requires representative views and may increase complexity

A major research challenge is achieving robustness without sacrificing discriminative information. Illumination normalization may reduce unwanted variation but can also suppress meaningful facial details, while local descriptors may preserve regional information but remain sensitive to pose and alignment errors. Consequently, combining global and local representations is a promising direction when the integration improves complementary information without introducing excessive redundancy.

Another challenge concerns realistic evaluation and generalization. Systems trained on controlled images may perform poorly when tested on images with different cameras, lighting conditions, resolutions, or subject behavior. Robust evaluation should therefore consider cross-condition recognition, computational cost, failure cases, and the consistency of performance across different datasets rather than relying solely on accuracy under controlled conditions.

8. RESEARCH DIRECTIONS

Future face recognition research should emphasize feature representations that preserve identity information while reducing sensitivity to illumination, pose, expression, and partial occlusion. Combining global appearance with local descriptors may provide a more comprehensive representation than relying on either approach independently. However, such combinations should be supported by systematic feature selection and evaluation to avoid unnecessary computational complexity.

Pose-aware and illumination-aware learning also remain important research directions. Multi-view training, photometric modeling, and invariant feature extraction can help systems accommodate variations that are difficult to address through conventional image matching. Further research should investigate how these techniques can be integrated into practical recognition systems with limited training data and computational resources.

Finally, evaluation should reflect the conditions under which face recognition systems are expected to operate. Benchmarking should include variations in pose, illumination, expression, image quality, and acquisition environment. Such evaluation can provide stronger evidence of recognition robustness and help distinguish genuine methodological improvements from performance gains limited to controlled datasets.

9. CONCLUSION

Face recognition has evolved through the development of global appearance representations, local feature descriptors, and classification strategies designed to distinguish identity under varying image conditions. Appearance-based methods provide efficient representations but are often sensitive to illumination and pose, whereas local features offer more detailed descriptions while introducing challenges in localization and matching. Illumination normalization and multi-view representations provide important mechanisms for improving robustness, although their effectiveness depends on the quality of the underlying features and training data.

The review indicates that reliable face recognition requires a balanced combination of discriminative representation, effective classification, and robustness to acquisition variations. Future research should prioritize complementary global and local features, pose- and illumination-aware methods, and realistic

evaluation protocols. These directions are essential for developing face recognition systems that remain dependable beyond controlled imaging environments.

REFERENCES

[1] M. Turk and A. Pentland, "Eigenfaces for recognition," *Journal of Cognitive Neuroscience*, vol. 3, no. 1, pp. 71–86, Jan. 1991, doi: 10.1162/jocn.1991.3.1.71.

[2] P. N. Belhumeur, J. P. Hespanha, and D. J. Kriegman, "Eigenfaces vs. fisherfaces: Recognition using class specific linear projection," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 19, no. 7, pp. 711–720, Jul. 1997, doi: 10.1109/34.598228.

[3] L. Shen and L. Bai, "A review on Gabor wavelets for face recognition," *Pattern Analysis and Applications*, vol. 9, no. 2–3, pp. 273–292, Sep. 2006, doi: 10.1007/s10044-006-0033-y.

[4] T. Ahonen, A. Hadid, and M. Pietikäinen, "Face description with local binary patterns: application to face recognition," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 28, no. 12, pp. 2037–2041, Dec. 2006, doi: 10.1109/TPAMI.2006.244.

[5] L. Wiskott, J. M. Fellous, N. Krüger, and C. Der Von Malsburg, "Face recognition by elastic bunch graph matching," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 19, no. 7, pp. 775–779, Jul. 1997, doi: 10.1109/34.598235.

[6] R. M. Makwana, "Illumination invariant face recognition: A survey of passive methods," *Procedia Computer Science*, vol. 2, pp. 101–110, 2010, doi: 10.1016/j.procs.2010.11.013.

[7] H. Han, S. Shan, X. Chen, and W. Gao, "A comparative study on illumination preprocessing in face recognition," *Pattern Recognition*, vol. 46, no. 6, pp. 1691–1699, Jun. 2013, doi: 10.1016/j.patcog.2012.11.022.

[8] O. Arandjelović and R. Cipolla, "Achieving robust face recognition from video by combining a weak photometric model and a learnt generic face invariant," *Pattern Recognition*, vol. 46, no. 1, pp. 9–23, Jan. 2013, doi: 10.1016/j.patcog.2012.06.024.

[9] R. Gross, S. Baker, I. Matthews, and T. Kanade, "Face recognition across pose and illumination," in *Handbook of Face Recognition*, New York: Springer-Verlag, 2005, pp. 193–216. doi: 10.1007/0-387-27257-7_10.

[10] X. Zhang and Y. Gao, "Face recognition across pose: A review," *Pattern Recognition*, vol. 42, no. 11, pp. 2876–2896, Nov. 2009, doi: 10.1016/j.patcog.2009.04.017.

[11] T. Sim, S. Baker, and M. Bsat, "The CMU pose, illumination, and expression database," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 25, no. 12, pp. 1615–1618, Dec. 2003, doi: 10.1109/TPAMI.2003.1251154.

[12] M. Yue, "Face recognition," *Proceedings - IEEE International Symposium on Circuits and Systems*, vol. 5, no. 4, pp. V-305-V–308, Dec. 2000, doi: 10.1145/954339.954342.