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Optimizing Face Recognition Accuracy through Eigenfaces and K-Nearest Neighbour: An Empirical Study

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تحسين دقة التعرف على الوجوه باستخدام الـ Eigenfaces وخوارزمية أقرب الجيران: دراسة تجريبية

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Abstract:

Face recognition has emerged as a cornerstone of computer vision research, spurred by its expansive utility in security systems, surveillance, and human-computer interaction. This study develops a robust face recognition framework that integrates the Eigenfaces methodology for sophisticated feature extraction with the K-Nearest Neighbour (KNN) algorithm for classification. By leveraging Principal Component Analysis (PCA), Eigenfaces are generated to significantly condense the dimensionality of facial datasets while preserving the most salient discriminative features. These optimized feature vectors are subsequently processed via a KNN classifier, utilizing a range of K values to perform a thorough evaluation of the system's operational performance. The empirical findings reveal that the proposed methodology yields high recognition accuracy alongside stable computational overhead, suggesting that the selection of an optimal K value is essential for balancing predictive precision and processing efficiency.

Keywords: Face Recognition (FR), Eigenfaces (EF), Principal Component Analysis (PCA), K-Nearest Neighbour (KNN), Feature Extraction.

الملخص

بَرَزَ التعرف على الوجوه كحجر زاوية في أبحاث الرؤية الحاسوبية، مدفوعاً بتطبيقاته الواسعة في أنظمة الأمن، والمراقبة، والتفاعل بين الإنسان والحاسوب. تطوّر هذه الدراسة إطاراً متكاملًا للتعرف على الوجوه يجمع بين منهجية الوجوه (Eigenfaces) لاستخراج السمات المتقدمة وخوارزمية أقرب الجيران (KNN) لإتمام عملية التصنيف. وباستخدام تقنية تحليل المكونات الرئيسية (PCA)، يتم توليد الوجوه لتقليل أبعاد مجموعات البيانات الوجهية بشكل كبير مع الحفاظ على أبرز السمات التمييزية. وتُعالج متجهات السمات المُحسّنة لاحقاً عبر مصنف (KNN)، مع اختبار مجموعة من قيم (K) لإجراء تقييم شامل لأداء النظام التشغيلي. وقد كشفت النتائج التجريبية أن المنهجية المقترحة تحقق دقة تعرف عالية بالتوازي مع استقرار الزمن الحسابي، مما يشير إلى أن اختيار القيمة المثلى للمعامل (K) يُعد أمراً جوهرياً لتحقيق التوازن بين دقة التنبؤ وكفاءة المعالجة.

الكلمات المفتاحية: التعرف على الوجوه (FR)، الوجوه (EF)، تحليل المكونات الرئيسية (PCA)، أقرب الجيران (KNN)، استخراج السمات.

1. Introduction

Face recognition is a biometric technique that identifies or verifies individuals based on their facial characteristics. Compared to other biometric modalities, face recognition is non-intrusive and can be performed using images acquired from standard cameras. However, face images are typically high-dimensional and

sensitive to variations such as illumination, facial expressions, and pose. These challenges make feature extraction and dimensionality reduction essential steps in building an effective face recognition system.

One of the most well-known appearance-based methods for face recognition is the Eigenfaces approach, which applies PCA to facial images. Eigenfaces project face images into a lower-dimensional subspace that captures the most significant variations among faces. Once features are extracted, a suitable classifier is required to perform recognition. Among various classifiers, the K-Nearest Neighbour (KNN) algorithm is widely used due to its simplicity and effectiveness in low-dimensional feature spaces.

This work implements and evaluates a face recognition system based on Eigenfaces and KNN. The system performance is analyzed in terms of recognition accuracy and computational time for different values of K. The main objective is to demonstrate the effectiveness of combining Eigenfaces with KNN and to determine an optimal K value for reliable face recognition.

2. Yale Face Database

The Yale Face Database is a widely used dataset in face recognition research. It contains grayscale images of multiple subjects captured under different lighting conditions, facial expressions, and slight pose variations. Each subject typically has several images, which allows researchers to evaluate the robustness of face recognition algorithms under real-world variations. The dataset is especially useful for testing Eigenfaces and PCA-based methods, as it highlights how well the system can capture the most discriminative facial features while ignoring irrelevant variations such as illumination or minor expression changes.

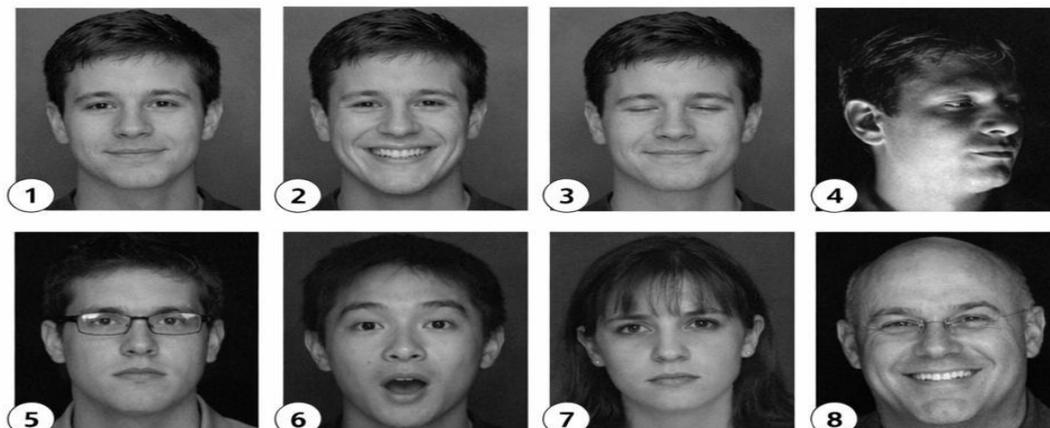


Figure 1: Examples of face images from the Yale Face Database showing variations in expression and lighting.

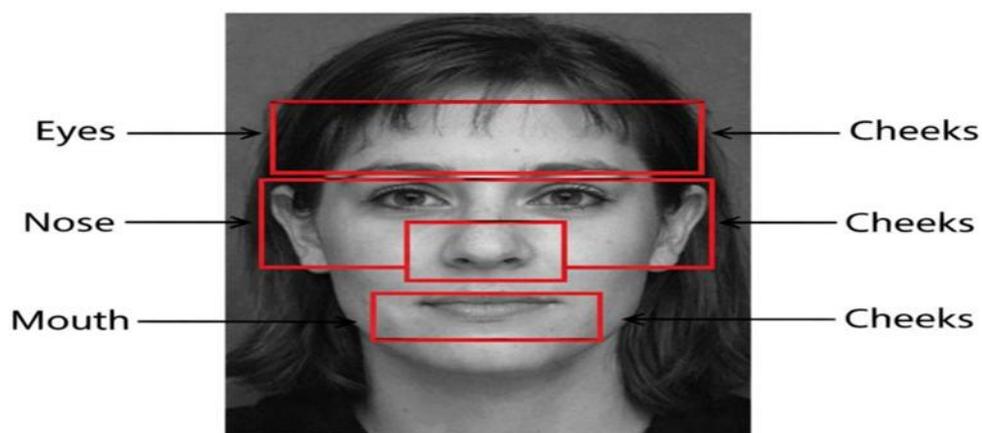


Figure 2: Key facial regions highlighted for feature extraction using Eigenfaces (eyes, nose, mouth, and cheeks marked with red rectangles).

3. Methodology

3.1 Experimental Setup

The dataset is initially constructed and divided into two disjoint subsets: a training set and a testing set. The application workflow begins with a preprocessing stage that focuses on feature selection. The standard deviation of all original features is computed, and features exhibiting a deviation of less than 10% are discarded. This reduces the number of retained features by eliminating low-variance features.

Subsequently, image normalization is applied to ensure consistency across the dataset and to improve recognition robustness. A second feature selection stage is then performed within the algorithm, again based on the standard deviation criterion. To further reduce computational complexity, a down-sampling step is incorporated, retaining every tenth feature from the previously selected feature set. This results in a more compact representation while preserving the most informative components.

The application is implemented in MATLAB. An auxiliary function is also developed for face detection, which accepts an input image, detects eye positions, and draws a red bounding box around the face.

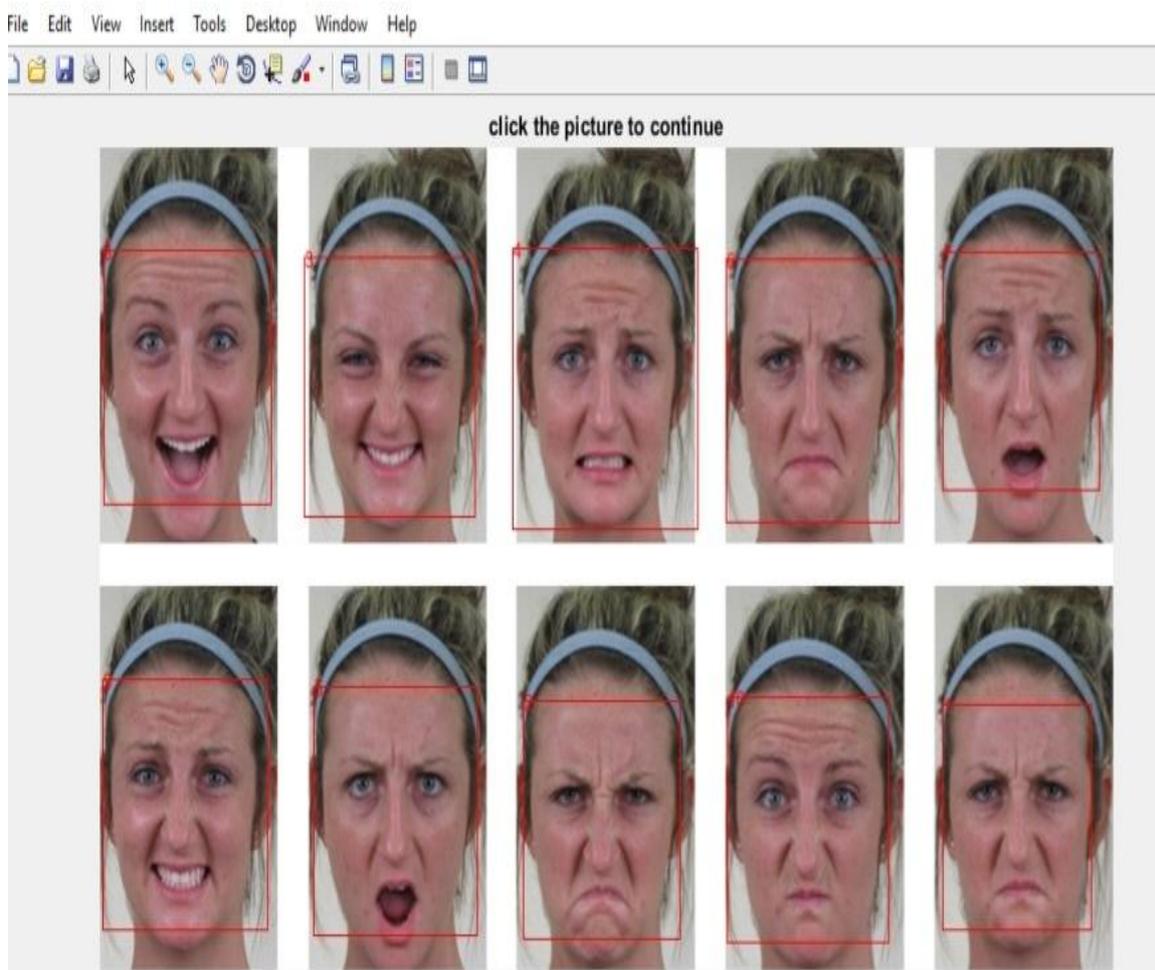


Figure 3: Screenshot from the application showing detected faces highlighted with red squares.

After detecting the faces, all identified facial regions are extracted and displayed in a separate panel for further processing.

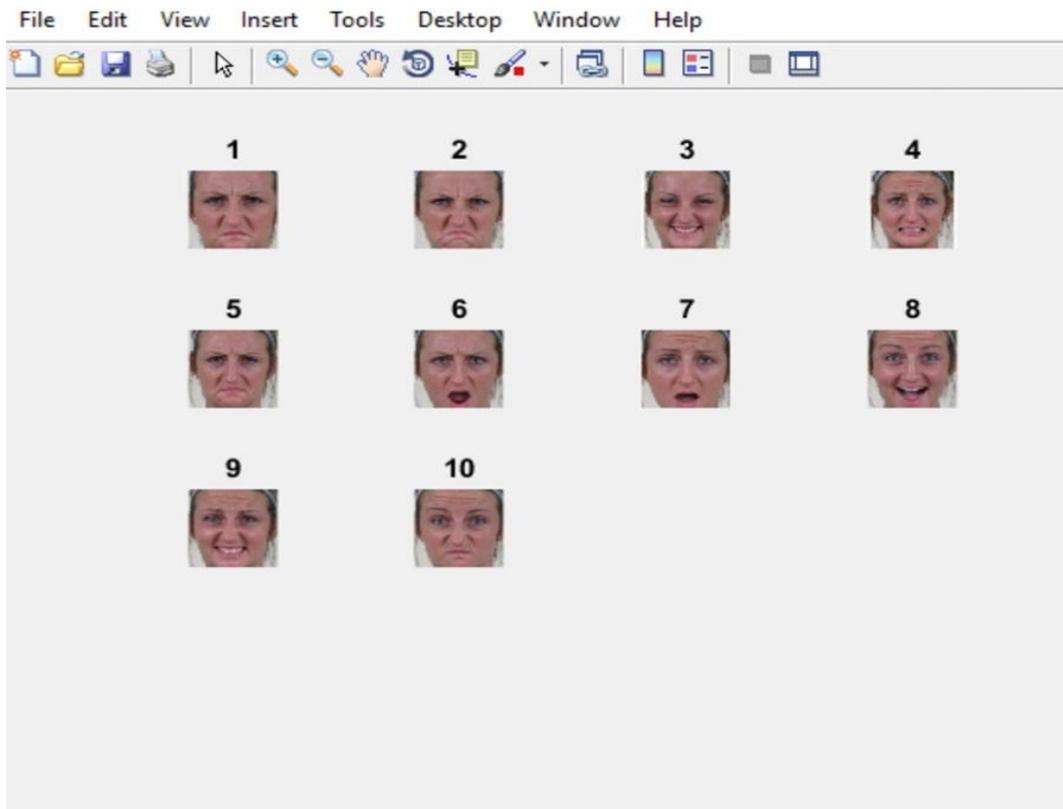


Figure 4: Facial regions detected in Figure 3, cropped and displayed collectively in a new panel.

3.2 Feature Extraction: Eigenfaces

The Eigenfaces method applies PCA to reduce the dimensionality of face images. Each face image is converted into a vector, and the mean face is computed from the training set. The mean face is subtracted from each image to normalize the data. A covariance matrix is constructed from the normalized images, and its eigenvectors corresponding to the largest eigenvalues are extracted.

These eigenvectors, called eigenfaces, represent the principal components of facial variations. Both training and testing images are projected onto the eigenface subspace, resulting in compact feature vectors that retain the most important discriminatory information. Different numbers of eigenfaces are evaluated to analyze their impact on recognition performance.

3.3 Classification: K-Nearest Neighbour

After feature extraction, classification is performed using the KNN algorithm. KNN assigns a class label to a test sample based on the majority class among its K closest training samples, using Euclidean distance as the similarity measure.

Different values of K are tested to study their effect on recognition accuracy and computational time. Selecting an appropriate K is crucial: a small K may be sensitive to noise, while a large K may reduce classification accuracy.

Note: The parameter K in the Eigenfaces method refers to the number of principal components, while K in the KNN classifier represents the number of nearest neighbors.

4. Experimental Procedure

A comprehensive preprocessing pipeline is applied in four stages:

- Partitioning the dataset into training and testing sets.
- Image normalization.
- Feature selection based on standard deviation.
- Down-sampling to reduce computational complexity.

For each experiment, 10 independent runs are conducted for different values of K (Eigenfaces dimensionality: 10, 20, 30). Each run consists of:

Selecting 45 training samples and 120 testing samples randomly.

- Applying preprocessing steps.
- Computing Eigenfaces using PCA.
- Classifying both training and testing samples with KNN.
- Calculating the misclassification rate (computed as $1 - \text{accuracy}$).

5. Results

The system's performance is evaluated on validation and test datasets. Table 1 summarizes recognition accuracy and computational time for different K values in KNN.

Table 1. Recognition Accuracy and Computational Time for Different K Values in KNN

K	Validation Accuracy (%)	Test Accuracy (%)	Time Taken (s)
1	97.46	97.09	871.38
3	97.56	97.30	918.73
4	97.67	97.37	917.79
7	97.50	97.15	917.83

Note: The K values in Table 1 correspond to the KNN classifier, while PCA dimensionality (Eigenfaces) is tested separately with K = 10, 20, 30.

6. Discussion

Recognition accuracy improves as K (KNN) increases up to an optimal point. The highest test accuracy of 97.37% is achieved at K = 4, indicating a balance between robustness and sensitivity to local variations. Beyond this, accuracy fluctuates minimally.

Computational time remains nearly constant, indicating that increasing K does not add significant complexity. These results confirm that combining Eigenfaces for dimensionality reduction and KNN for classification provides an effective and efficient face recognition solution.

7. Conclusion

This paper presented a face recognition system combining Eigenfaces and K-Nearest Neighbour (KNN) techniques. By using Eigenfaces, the system successfully reduced the dimensionality of facial images while retaining the most discriminative features, enabling efficient and focused analysis. KNN served as a reliable classifier in the transformed feature space, and experimental results confirmed high recognition accuracy, with K = 4 identified as the optimal parameter.

The proposed approach proves to be simple, efficient, and highly applicable to practical scenarios such as security monitoring, surveillance systems, and human-computer interaction applications. The study also emphasizes the critical role of proper preprocessing, feature extraction, and parameter selection in achieving consistent and robust performance.

In conclusion, this work demonstrates that combining dimensionality reduction methods with effective classification techniques provides a powerful and practical solution for face recognition challenges, paving the way for further enhancements and applications in real-world environments.

8. References

1. Turk, M., & Pentland, A. (1991). Eigenfaces for Recognition. *Journal of Cognitive Neuroscience*, 3(1), 71–86.
2. Tamimi, A. A., Al-Allaf, O. N., & Alia, M. A. (2015). Eigen Faces and Principal Component Analysis for Face Recognition Systems: A Comparative Study. *International Journal of Computers & Technology*, 14(4), 5650–5660.

3. Stephen, E. A. (2025). Image Preprocessing for Face Recognition. *Journal of Computing and Electronic Information Management*, 19(1), 20–29.
4. Evaluation of face recognition techniques using PCA, wavelets and SVM. (2010). *Expert Systems with Applications*, 37(9), 6404–6408.
5. Past, Present, and Future of Face Recognition: A Review. (2020). *Electronics*, 9(1188).
6. Kshirsagar, V. P., Baviskar, M. R., & Gaikwad, M. E. (2011). Face Recognition Using Eigenfaces. ICCRD 2011.
7. An efficient approach for face recognition based on common eigenvalues. (2014). *Pattern Recognition*, 47(5), 1869–1879.
8. Bora, P. K., Rahman, F., & Hazarika, M. (2015). A Review on Face Recognition Approaches. *IJERT*, 4(05).