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CẢI THIỆN NHẬN DIỆN CẢM XÚC KHUÔN MẶT THÔNG QUA PCA VÀ LBP KẾT HỢP VỚI BỘ PHÂN LOẠI SVM

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TỪ KHÓA

Nhận dạng biểu cảm khuôn mặt;
Phân tích thành phần chính;
Mẫu nhị phân cục bộ;
Máy vector hỗ trợ;
Khoảng cách Euclid.

TÓM TẮT

Bài báo này đề xuất phương pháp nhận diện biểu cảm khuôn mặt (FER) sử dụng các thuật toán phân tích thành phần chính (PCA) và mẫu nhị phân cục bộ (LBP) để trích xuất đặc trưng từ hình ảnh khuôn mặt. Các thí nghiệm được thực hiện trên hai bộ dữ liệu: Biểu cảm khuôn mặt phụ nữ Nhật Bản (JAFFE) và Cohn-Kanade Extended (CK+). Máy vector hỗ trợ (SVM) được sử dụng làm bộ phân loại chính so với khoảng cách Euclid (L2) để đánh giá hiệu suất của các phương pháp phân loại. Kết quả thí nghiệm cho thấy sự kết hợp giữa PCA và SVM đạt tỷ lệ nhận diện 87% trên cơ sở dữ liệu JAFFE và 81% trên CK+ với sự khác biệt do tính chất phức tạp và sự đa dạng của bộ dữ liệu CK+. Kết quả chỉ ra rằng phương pháp PCA và LBP kết hợp với SVM mang lại hiệu quả vượt trội so với các phương pháp sử dụng khoảng cách Euclid, chứng tỏ SVM là bộ phân loại hiệu quả cho FER trong các môi trường thử nghiệm phức tạp.

IMPROVING FACIAL EXPRESSION RECOGNITION THROUGH PCA AND LBP WITH SVM CLASSIFIER

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ABSTRACT

This paper proposes a facial expression recognition method using a combination of Principal Component Analysis (PCA) and Local Binary Pattern (LBP) algorithms for feature extraction from facial images. Experiments were conducted on two datasets: the Japanese Female Facial Expression (JAFFE) database and the Cohn-Kanade Extended (CK+) database. Support Vector Machine (SVM) was used as the primary classifier, compared to Euclidean distance (L2), to evaluate the performance of the classification methods. The experimental results show that the combination of PCA and SVM achieves a recognition rate of 87% on the JAFFE database and 81% on the CK+ database, with the difference attributed to the complexity and diversity of the CK+ dataset. The study indicates that the PCA and LBP method combined with SVM, outperforms methods using Euclidean distance, demonstrating that SVM is an effective classifier for facial expression recognition in complex experimental setting.

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1. INTRODUCTION

The advancement of robotics in various domains such as security, entertainment, healthcare, and domestic life has significantly increased the demand for research in image processing and pattern recognition [1–2]. In the context of Human-Computer Interaction (HCI), the ability to interpret gestures and facial expressions enables robots to communicate more naturally, thereby enhancing collaboration efficiency with humans across diverse tasks [3]. This not only improves user experience but also unlocks numerous potential applications for artificial intelligence in everyday life.

Ekman's study [4] introduced the Facial Action Coding System (FACS), a well-known method for representing and analyzing facial expressions. This system describes every facial muscle movement through 46 Action Units (Aus), each corresponding to the activity of a specific group of facial muscles responsible for forming distinct facial morphologies. Thus, a facial expression is essentially a combination of multiple Aus. Facial expressions are categorized into six basic emotional groups: surprise, sadness, anger, happiness, disgust, and fear [5], which are considered universal expressions used by humans to convey emotions. In certain cases, the neutral state is also included along with these six expressions.

Although robots can simulate the process of Facial Expression Recognition (FER) similar to humans, they still encounter significant challenges in accurately identifying emotions. This is primarily due to the dynamic nature of facial expressions, which continuously change over time, whereas humans can produce an infinite variety of expressions differing in complexity, intensity, and meaning. To address this challenge, numerous recognition algorithms have been studied and proposed. Various databases have also been utilized in FER research, such as the Maja and Michel Initiative (MMI) dataset [6], which includes both spontaneous and posed expressions; the Japanese Female Facial Expression (JAFFE) dataset [7], which focuses on female subjects; and the Cohn-Kanade Extended (CK+) dataset [7], which is among the most commonly used benchmarks in this domain.

The FER process typically comprises three main stages: face detection, expression feature extraction, and expression classification [8]. First, the system must determine whether a face is present in the image or video frame and, if so, identify its position and size. This step is crucial as it focuses on the region containing relevant information while eliminating unrelated background elements. Next, the system extracts the most significant features related to facial expressions, such as the positions of the eyebrows, eyes, mouth, and facial contours. These features play a fundamental role in distinguishing between different expressions. Finally, machine learning algorithms or recognition models are employed to analyze the extracted data and classify the facial expression into an emotional category, such as happiness, sadness, anger, or surprise [8]. Each step in this process is critical and directly impacts the system's accuracy. To improve recognition performance, modern approaches often integrate advanced techniques such as Deep Learning, Convolutional Neural Networks (CNN), or Support Vector Machine (SVM) models to better handle variations in lighting conditions, viewing angles, and complex facial expressions.

The structure of this paper is organized as follows: Section 1 provides an overview of the importance of FER in real-world applications. It also discusses the challenges in FER, particularly the complex temporal variations of facial expressions; Section 2 presents a summary of feature extraction techniques, with a brief introduction to two commonly used methods: Local Binary Pattern (LBP) and Principal Component Analysis (PCA); Section 3 introduces the datasets utilized in the experiments; Section 4 details the proposed methodology, including the processing pipeline and the applied model; Section 5 presents and analyzes the experimental results, comparing the performance of various approaches; Finally, Section 6 concludes the paper by summarizing the key findings of the study.

2. FEATURE EXTRACTION TECHNIQUES

Facial feature extraction techniques play a crucial role in expression recognition, aiming to compute essential and distinctive characteristics from the face while minimizing the amount of data that needs to be processed. The choice of feature extraction method directly impacts recognition accuracy and computational efficiency. To extract key features from digital images or facial video sequences, numerous methods have been proposed. These approaches can generally be categorized into two main groups: geometry-based techniques and appearance-based techniques.

Geometry-based methods focus on computing the geometric distances between AUs extracted from the face. Key facial features are determined based on the relative positions and sizes of various facial components. The objective of this approach is to accurately model facial muscle movements and the variations in facial expressions. Representative algorithms in this category include Elastic Bunch Graph Matching [9], Active Shape Model, and Active Appearance Model [10]. These algorithms primarily facilitate the identification and comparison of geometric features across different facial regions.

In contrast, appearance-based methods utilize and process the entire facial image, applying linear transformations or statistical techniques to identify fundamental feature vectors that represent the face. These methods are capable of detecting complex visual patterns and providing a more in-depth description of expressive facial components. Prominent algorithms in this category include PCA [11], a well-known dimensionality reduction technique that preserves the most significant facial features, and LBP [12], a widely used texture descriptor in facial recognition. These approaches produce stable and discriminative visual features that are highly applicable in both face and expression recognition tasks.

2.1 Principal Component Analysis

PCA is a widely used dimensionality reduction technique in image processing and pattern recognition.

PCA operates by transforming the original data into a new coordinate system, where the principal components are ordered according to their contribution to the total variance. The process involves several key steps: data normalization to ensure all features have equal weight, computation of the covariance matrix to identify relationships among variables, extraction of eigenvalues and eigenvectors to determine the most significant directions in the data, selection of the principal components with the highest eigenvalues, and finally, projection of the data into the new subspace to reduce dimensionality while retaining essential information [11]. Thanks to its effective feature extraction capabilities, PCA is widely applied in face recognition and FER. In the context of FER, PCA helps reduce the dimensionality of facial images, thereby optimizing recognition speed [13]. It also supports the discrimination of different emotional states by retaining the most relevant features associated with facial expression changes [14]. Furthermore, PCA is used for image compression and noise reduction, preserving critical details while enhancing data storage and processing efficiency. However, a notable limitation of PCA is its inability to preserve nonlinear information within facial data. Consequently, it is often combined with other algorithms such as LBP or SVM to improve recognition accuracy in FER tasks.

2.2 Local Binary Pattern

LBP is a widely used feature extraction technique in facial recognition. The method begins by dividing the facial image into small regions and then analyzing each pixel based on the grayscale value of its surrounding neighbors relative to the central pixel. Neighboring pixels are thresholded into binary values either 1 or 0 depending on whether their intensity is greater or less than that of the central pixel. As a result, a binary pattern is generated for each pixel within the analyzed region [12]. Subsequently, frequency histograms are constructed for each region using 256 bins to represent the different binary values. These histograms are then concatenated to form a comprehensive feature vector for the entire facial image. This process produces highly stable binary features that are effective for image analysis and FER. To enhance feature quality, the most effective LBP features are selected using the AdaBoost algorithm [15]. AdaBoost is a powerful machine learning technique that optimizes the feature selection process, thereby improving the classification and recognition capabilities of the system.

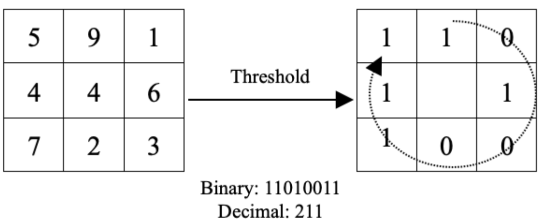

Figure 1. *Example of LBP Operator in Action*

Initially, the LBP technique employs a 3×3 neighborhood in which each pixel is encoded into an 8-bit value based on its eight surrounding neighbors. Specifically, the LBP operator assigns a binary value to each neighboring pixel by comparing its grayscale intensity with that of the central pixel: if the neighbor's value is greater than or equal to the center, it is assigned a value of 1; otherwise, it is set to 0. This results in a binary number representing each pixel in the image.

However, a key limitation of the basic LBP operator lies in the small size of the 3×3 neighborhood, which restricts its ability to capture larger-scale texture features across the facial structure. To address this limitation, LBP has been extended to incorporate neighborhoods of varying sizes, enabling the modeling of texture features at multiple scales [12]. One significant enhancement to LBP is the concept of uniform patterns. An LBP pattern is considered uniform if its binary representation contains at most one transition from 0 to 1 or from 1 to 0 when read in a circular fashion. Examples of such patterns include 00000000, 11111111, 00011000, and 11111001.

Statistics have shown that uniform patterns account for approximately 90% of all patterns in a (8,1) neighborhood and around 70% in a (16,2) neighborhood when applied to texture images [16]. Here, the notation (P, R) denotes a neighborhood consisting of P sampling points uniformly distributed on a circular radius R, forming a set of circularly symmetric pixels. The use of uniform patterns significantly reduces the number of features to be processed while preserving essential structural information, thereby enhancing the recognition performance in facial expression classification tasks.

3. FACIAL EXPRESSION DATABASES

3.1 JAFFE Dataset

The JAFFE dataset [17] is one of the most widely used datasets in FER research. It consists of 213 grayscale images from 10 Japanese female subjects, each portraying one of seven facial expressions: anger, happiness, neutral, surprise, sadness, fear, and disgust. Figure 2 illustrates a sample of images from the JAFFE dataset.

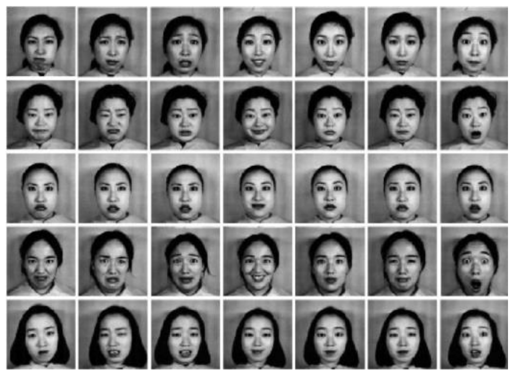

Figure 2. *Facial expression samples from the JAFFE dataset.*

All images in the JAFFE dataset have been preprocessed to standardize format and enhance image quality, thereby improving the accuracy of subsequent analysis. JAFFE offers a controlled environment with clearly defined and consistent facial expressions, making it a valuable resource for evaluating the performance of FER models.

3.2 CK+ Dataset

The CK+ dataset [18] is one of the largest and most comprehensive datasets in the field of facial expression analysis. It contains 10,708 high-resolution images (640×490 pixels) that capture the progression of facial expressions from a neutral state to one of six emotional expressions: happiness, fear, sadness, anger, surprise, and disgust. CK+ provides not only static images but also temporal image sequences, allowing for the study of facial expression dynamics over time.

This temporal aspect makes CK+ a valuable resource for analyzing the transitions and intensity variations in facial expressions. In this study, we selected clearly labeled and high-quality images from the CK+ dataset to conduct our experiments.

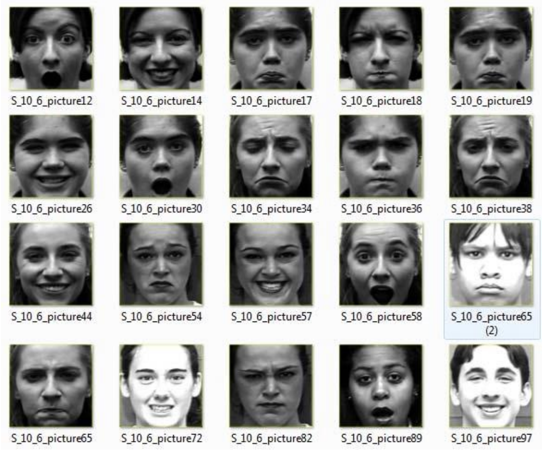

Figure 3. *Sample facial expression images from the CK+ dataset*

4. PROPOSED METHOD

This section describes the methodology employed in this study. Two facial expression datasets, JAFFE and CK+, were used. The images from both datasets were split into training and testing sets to ensure objectivity during model evaluation. For the feature extraction step, two main algorithms were applied: PCA and LBP. Specifically, in the LBP method, a uniform LBP with radius 1 and 8 neighboring points (8,1) was used to extract texture features from the facial images. Two different scenarios were tested to evaluate the effectiveness of the method: LBP1, in which the facial image was divided into 16 sub-regions, and LBP2, where the image was divided into 64 sub-regions to capture finer facial details. To provide a clearer illustration of the proposed method, Figure 4 presents a block diagram outlining the entire process from data preprocessing and feature extraction to the final facial expression classification stage.

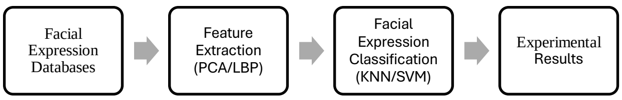

Figure 4. *Block diagram of the proposed method workflow*

In the classification stage, two methods were employed to compare FER performance: Euclidean distance (L2) and SVM. Each method adopts a distinct approach in determining the facial expression label based on the extracted features.

For the JAFFE dataset, a total of 137 images were selected for training the model, while the remaining 76 images were used for testing and evaluating model accuracy. For the CK+ dataset, 315 images were selected and used for both training and testing, reflecting the dataset's specific structure in FER performance evaluation. Conducting experiments on both datasets allows for assessing the generalizability of the model when applied to datasets with varying characteristics.

5. EXPERIMENTAL RESULTS

The experiments were conducted in MATLAB, using two facial expression datasets, JAFFE and CK+, to evaluate FER performance. All images from these datasets were converted to grayscale to reduce color-related noise and optimize the feature extraction process. The images were saved in TIFF format to preserve image quality during processing. For the JAFFE dataset, 64% of the images were used for training, while the remaining 36% were used as the test set to evaluate the model. In the CK+ dataset, the data was equally divided, with 50% for training and 50% for testing, ensuring a balanced evaluation across both datasets. This approach allows for assessing the generalization ability of the model when handling various facial expressions from different data sources. To demonstrate and compare the performance of the proposed algorithms, PCA and LBP features were extracted from the images, while SVM and K-Nearest Neighbour (KNN) using Euclidean distance (L2) were employed to classify the facial expression images.

The experimental results are presented through confusion matrices in the following tables, highlighting the significant differences in FER performance when applying various feature extraction techniques and classifiers across the JAFFE and CK+ datasets. When comparing the performance of PCA+L2 and PCA+SVM, the results for the JAFFE dataset are shown in Table 1 and Table 3, while those for the CK+ dataset are presented in Table 2 and Table 4. Observing the results, it is evident that SVM outperforms Euclidean distance (L2) in most scenarios. Specifically, with PCA+SVM, the recognition rate on the JAFFE dataset reaches nearly 100% for certain expressions, while the CK+ dataset achieves around 87%, indicating that SVM offers superior classification performance compared to L2, especially on more homogeneous datasets like JAFFE. In contrast, the CK+ dataset, which includes both male and female subjects and a wider variety of expressions, presents a higher level of complexity, leading to a slightly lower recognition rate, yet still producing reasonably good results.

Table 1. *Confusion Matrix for FER using PCA+L2 on the JAFFE Dataset.*

PCA+L2	Neutral	Angry	Disgust	Fear	Happy	Sad	Surprise
Neutral	**80**	0	0	0	0	8	12
Angry	0	**90**	0	3	7	0	0
Disgust	0	8	**65**	16	11	0	0
Fear	1	0	8	**82**	1	7	0
Happy	7	1	2	6	**70**	7	6
Sad	15	15	0	0	15	**54**	0
Surprise	0	0	0	0	2	8	**90**

Table 2. *Confusion Matrix for FER using PCA+L2 on the CK+ Dataset.*

PCA+L2	Neutral	Angry	Disgust	Fear	Happy	Sad	Surprise
Neutral	**60**	1	5	4	8	13	9
Angry	2	**58**	18	2	2	15	2
Disgust	2	4	**69**	10	6	9	10
Fear	7	2	2	**65**	9	2	12
Happy	5	5	5	0	**71**	10	3
Sad	18	4	7	2	4	**64**	0
Surprise	2	5	2	4	2	1	**83**

Table 3. *Confusion Matrix for FER using PCA+SVM on the JAFFE Dataset.*

PCA+SVM	Neutral	Angry	Disgust	Fear	Happy	Sad	Surprise
Neutral	**99**	0	0	0	0	0	1
Angry	0	**100**	0	0	0	0	0
Disgust	0	7	**75**	18	0	0	0
Fear	0	0	5	**95**	0	0	0
Happy	15	0	0	0	**75**	10	0
Sad	0	0	0	8	2	**90**	0
Surprise	0	0	0	0	2	6	**92**

Table 4. *Confusion Matrix for FER using PCA+SVM on the CK+ Dataset.*

PCA+SVM	Neutral	Angry	Disgust	Fear	Happy	Sad	Surprise
Neutral	**70**	0	0	13	0	11	0
Angry	0	**75**	11	0	0	13	0
Disgust	4	9	**75**	5	0	8	7
Fear	2	2	3	**70**	0	5	18
Happy	0	5	1	0	**88**	8	0
Sad	0	13	7	2	0	**78**	0
Surprise	0	0	7	10	2	0	**80**

Table 5. *Confusion Matrix for FER using LBP1+L2 on the JAFFE Dataset.*

LBP1+L2	Neutral	Angry	Disgust	Fear	Happy	Sad	Surprise
Neutral	**74**	0	0	10	0	10	0
Angry	2	**74**	11	0	0	10	3
Disgust	9	0	**80**	2	2	8	7
Fear	3	0	3	**78**	0	6	10
Happy	7	4	2	0	**87**	0	0
Sad	5	9	7	0	0	**80**	0
Surprise	0	2	0	2	0	10	**85**

Tabel 6. *Confusion Matrix for FER using LBP1+L2 on the CK+ Dataset.*

LBP1+L2	Neutral	Angry	Disgust	Fear	Happy	Sad	Surprise
Neutral	**82**	0	2	3	3	8	1
Angry	5	**73**	10	3	2	5	2
Disgust	2	2	**86**	1	3	4	0
Fear	0	0	0	**78**	2	2	18

Happy	14	0	3	0	**73**	5	2
Sad	2	2	4	4	4	**80**	2
Surprise	2	3	1	3	3	2	**84**

Table 7. *Confusion Matrix for FER using LBP2+L2 on the JAFFE Dataset.*

LBP2+L2	Neutral	Angry	Disgust	Fear	Happy	Sad	Surprise
Neutral	**100**	0	0	0	0	5	5
Angry	5	**90**	5	0	0	0	0
Disgust	0	15	**85**	0	0	0	0
Fear	5	6	5	**80**	2	1	5
Happy	6	2	3	5	**55**	20	8
Sad	0	3	3	3	15	**76**	0
Surprise	0	0	0	5	5	0	**90**

Table 8. *Confusion Matrix for FER using LBP2+SVM on the JAFFE Dataset.*

LBP2+SVM	Neutral	Angry	Disgust	Fear	Happy	Sad	Surprise
Neutral	**84**	2	5	0	5	3	3
Angry	0	**73**	8	0	2	7	9
Disgust	4	0	**89**	2	0	2	2
Fear	2	7	0	**75**	6	0	10
Happy	2	2	9	0	**82**	0	4
Sad	10	16	2	2	2	**67**	0
Surprise	7	0	2	10	0	2	**78**

When analyzing the results of LBP1+L2 (Table 5, Table 6) and LBP2+L2 (Table 7, Table 8), it can be observed that increasing the number of sub-regions in the LBP (LBP2) significantly improves accuracy, especially on the JAFFE dataset. This indicates that enhancing the level of detail in feature extraction allows the system to better recognize facial expressions. Furthermore, when combining LBP2 with SVM (Table 8), the overall accuracy is improved compared to using L2, further confirming the effectiveness of SVM in expression classification. Experimental results show that both PCA and LBP perform well when combined with SVM, with higher recognition rates on JAFFE compared to CK+ due to subject consistency and controlled imaging angles. Although CK+ is more complex, it still achieves good results, demonstrating the generalization capability of the system. Enhancing feature extraction, such as using LBP2 instead of LBP1, also contributes to improved recognition performance.

6. CONCLUSION

This paper evaluates the performance of a FER system using two datasets: JAFFE and CK+. In the study, two feature extraction techniques PCA and LBP are applied, while the classification process is performed using SVM and KNN with Euclidean distance (L2). The experimental results show that both PCA and LBP achieve high performance when combined with SVM, significantly outperforming the Euclidean distance-based classifier. Additionally, the recognition accuracy on the JAFFE dataset is higher than that on CK+, partly because JAFFE includes only female subjects, ensuring gender consistency. In contrast, CK+ features more diverse subjects, increasing the complexity of FER.

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