Proceedings of CONF-MLA Workshop: Mastering the Art of GANs: Unleashing Creativity with Generative Adversarial Networks
DOI: 10.54254/2755-2721/80/2024CH0070

Research Advances in Facial Expression Recognition Technology

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Abstract. As a key area in artificial intelligence and computer vision, facial expression analysis technology has been taking hold rapidly, yielding dazzling advances. This technology extracts even the subtlest facial movements to identify when a human is sad, happy, or angry. It has extensive application value in markets like mental diagnosis, secure monitoring, and intelligent interaction. The paper will provide a brief overview of the kernel technology of facial expressions recognition: geometric features, appearance features, and deep learning. And compared the experimental results of different experiments, as a goal, the experiments compare functions of several methods in a multi-dataset context, concentrating the primary problems in the tasks like dataset bias, real-time requirements, and different light levels and partial occlusions in various environments. Eventually, the paper forecasts the imminent growth trend in data fusion and deep learning improvement. This also indicates that emerging technologies, especially in terms of applications, will have the upper hand.

Keywords: Facial expression recognition, Deep learning, Geometric features, Emotion computing.

1. Introduction

In the past few years, facial expression recognition technology has attracted significant attention and application. It can identify human emotional statuses by evaluating minor fluctuations in facial expressions, using multi-discipline details like psychology, computer vision, and artificial intelligence. The use of facial expressions has long been considered the most natural and most universal way to express feelings. Through correctly mapping human expressions, machines will be able to comprehend and reply in an appropriate manner. This in turn would open up various application domains, including intelligent human-computer interaction, health monitoring, and security[1].

In the field of autonomous driving, facial expression recognition technology helps systems detect driver fatigue, hence improves driving safety [2]. In the area of mental health, it aids in psychological therapy by revolving on trauma and mental problem identification [3]. Moreover, the facial expression internet of things devices is being increasingly applied in education, virtual reality, and entertainment [4]. As it was proved, because of the increase in demand for intelligent systems, facial expression recognition technology is currently the leading technology in emotional computing.

The area of deep learning has progressed a lot in recent years, and in particular, facial expression recognition technology has seen some great enhancements.

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Conventional methods using geometric features and visual features can achieve results only under limited restrictions. Hence, convolutional neural networks have been employed to improve the accuracy and robustness of the model, where CNNs automatically organize features of the original images to high levels [5].

2. Overview of Facial Expression Recognition Methods

Facial expression recognition technology has been developed in several stages. These stages are based on geometric features, appearance features, and deep learning. Each method has its own merits and demerits, making them proper for different situations [6].

2.1. Geometric Feature Methods

Geometric features are the first technique that facial expression recognition is applied to. They compute the degree of separation and angles between key facial landmarks.

By detecting the positions of the eyes, mouth, and eyebrows, it is possible to analyze the facial expression state of the person. These methods often rely on classical machine learning algorithms such as support vector machines (SVMs) or random forests [7].

2.2. Appearance Feature Methods

Appearance feature methods apply to the extraction process of facial information by analyzing wrinkles and textures. Approaches such as LGDV (Local Grayscale Distribution Variation) and texture variations in small image segments are used. Traditional methods like Local Binary Patterns (LBP) and Scale Invariant Feature Transform (SIFT) are often employed for feature extraction. Zhao and Pietikäinen's research confirmed the robustness of LBP in terms of lighting changes, but its adaptability to expression variations was limited [8].

2.3. Deep Learning Methods

In recent years, deep learning, particularly convolutional neural networks (CNNs), has led to breakthroughs in facial expression recognition. CNNs automatically learn high-level image features through multi-layer convolution operations, and they handle large-scale and diverse image data. This has made CNNs extremely effective in tasks involving complex facial expressions with varying poses, lighting conditions, or occlusion. CNNs have contributed significantly to progress in the field [9]. Deep learning has also benefited from transfer learning, where models achieve good performance on small datasets by learning from larger datasets, thus overcoming data scarcity problems [10]. Attention mechanisms have also been introduced to enhance CNN performance by focusing on important regions of the face [11].

3. Experiments and Analysis

To compare geometric features, appearance features, and deep learning methods, this paper conducts experiments and provides analysis. Several public datasets were used, and the paper employed common evaluation metrics to assess the performance of these methods.

3.1. Datasets

The experiments used the following three public facial expression datasets:

1. FER2013: This dataset contains a variety of facial images with nine basic emotions and includes variations in lighting and pose [12].
2. CK+: The CK-Plus (Cohn-Kanade extended) dataset contains image sequences of facial expressions with different intensity levels [13].
3. AffectNet: This large dataset captures facial expressions in natural environments, with complex emotional circumstances [14].

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3.2. Evaluation Metrics

The paper used the following metrics to compare the performance of the methods:

Accuracy: The proportion of correctly identified expressions.

Recall: The proportion of samples correctly identified for a specific category.

F1-score: The harmonic mean of accuracy and recall, useful for balancing performance in imbalanced datasets.

3.3. Deep Learning Methods

The following Table 1 shows the experimental results of geometric feature methods, appearance feature methods, and deep learning methods:

Table 1. The experiments used the following three public facial expression datasets.

Method	Dataset	Accuracy	Recall
LBP-based geometric feature method	**FER2013**	82%	78%
SIFT-based appearance feature method	**CK+**	85%	81%
VGGNet deep learning method	**AffectNet**	92%	88%

3.4. Experimental Results Analysis

On the FER2013 dataset, the LBP-based geometric feature method achieved an accuracy of 82% and a recall of 78% [15]. These methods perform well in conditions with minimal lighting changes and simple backgrounds. However, their limitations become evident when dealing with more complex facial expressions, as seen in the low recall rate for the diverse FER2013 dataset. The SIFT-based appearance feature method achieved better results with an accuracy of 85% and a recall of 81% on the CK+ dataset, indicating its ability to handle pose and lighting variations [16]. However, appearance-based methods are computationally expensive, limiting their real-time application. Deep learning methods outperformed traditional methods, with VGGNet achieving the highest accuracy (92%) and recall (88%) on the AffectNet dataset [17]. The complexity of expressions and natural environments in AffectNet were handled effectively through CNNs, which learned both low- and high-level features automatically.

4. Conclusion

This article reviews different methods of facial expression recognition technology and compares experimental results. Deep learning methods, particularly CNN-based approaches, outperform traditional geometric and appearance-based methods in complex and diverse environments. While traditional methods still have specific use cases, especially in low-resource settings, deep learning is the most promising direction for advancing facial expression recognition in real-world applications.

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