The Fuzzy Emotion Recognition Framework Using Semantic-Linguistic Facial Features

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***Abstract*—Emotion recognition through facial expression analysis is an emerging research in Artificial Intelligence which faces many challenges. The problem is the variation of facial expressions that displays human emotions. Humans can subjectively express the same emotions in various ways. To overcome the problem of ambiguity in emotion expression, a fuzzy approach is developed to analyze the facial components in determining the type of emotion. In this study, we proposed a framework for fuzzy emotion recognition as a representation of the psychologist knowledge. Three stages in the fuzzy emotion recognition were facial feature extraction with Active Appearance Model; Semantic-linguistic facial features extraction; fuzzy emotion recognition with Fuzzy Emotion Classification. System performance testing provided the best results on extended Cohn Kanade (CK+) facial expression dataset, with the accuracy of linguistic facial component recognition 0.98, and accuracy of fuzzy emotion recognition 0.90. Testing was also performed on custom-made Indonesian Mixed Emotion Dataset (IMED) which resulted in accuracy of 0.87. The fuzzy emotion recognition has a potential to be applied in various real problems such as virtual counseling, stress detection, lie detection, and e-commerce.**

Keywords*— *fuzzy emotion, facial expression, facial components, semantic features, linguistic features

I. INTRODUCTION

In the last decade, facial expression analysis has become a major topic of interest in Artificial Intelligence (AI). The main goal is to create an intelligent machine that able to understand human behaviour. Facial expressions provide information about human emotions as much as 55%, while verbal conversations provide information by 38% and other nonverbal cues such as gesture, eye movement, and intonation provide information by 7% [1]. Automatic facial expression analysis has many challenges as well as potential applications, such as in emotion recognition, human and computer interaction, behaviour analysis, detection of fatigue, health treatment, entertainment, and education [2].

Several studies in emotion recognition that have been carried out give optimistic results [3]. However, further research must still be needed to improve the efficiency and effectiveness of the emotion recognition system. Emotion recognition research conducted by [4], [5] recognizing basic emotions consisting of six categories: sad, happy, surprised, angry, disgust, and fear. Basic emotion recognition research claimed that only basic emotions can be categorized because they have clear and concise distinguishing characteristics. But in reality humans are able to recognize and express many mixed emotions. According to psychologists [6], mixed emotions are the combination of two or more basic emotions appear simultaneously or with the transition between basic emotions in a quick time interval.

Research on the recognition of mixed emotions has been carried out by [7] to recognize basic emotions and compound emotion on facial images. Classification was done for as many as 21 emotion classes consisting of 6 basic emotions and 15 compound emotions which were a combination of two different basic emotion classes. Mixed emotion research still remained a challenge and less explored for multiple emotions in a single occurrence. Emotion recognition research has been carried out using Machine Learning approach such as Support Vector Machine classifiers [1], Neural Network [8], and Deep Learning [9]–[11]. In that study, the recognition was applied to discrete basic emotions classification with fixed input values.

In our preliminary study, we tested our recognition system on a single custom-made dataset, we got satisfying result with 88.52% in accuracy rate on IMED dataset by using semantic facial features [12]. We also investigated the psychological knowledge to develop a fuzzy emotion recognition model based on psychological perspective [13]. In this study, we expand the framework by involving semantic and linguistic facial feature. Furthermore, the objective of this study is to measure the robustness of the proposed framework on other datasets to find out the trend of recognition rate on different facial expressions datasets.

This study aims to: 1) design a framework architecture of emotion recognition based on the concept of fuzzy emotion using the rules from psychologist; 2) extract semantic features of facial components for emotion recognition based on fuzzy emotion concepts; 3) develop a fuzzy inference system to analyze the linguistic conditions of facial components; 4) develop a fuzzy inference system for fuzzy emotion recognition; and 5) evaluate the robustness of fuzzy emotion recognition framework tested on various facial expression dataset.

II. EMOTION RECOGNITION FUNDAMENTALS

In this chapter we discuss about three fundamental concepts in emotion recognition which based on facial expression image analysis, i.e. human emotion; facial expression and fuzzy emotion; and image representation.

A. Human Emotion

The combination of several nonverbal cues can convey a strong message about human emotion. Emotion is an important element in social interaction where it shows a response in communication. According to Darwin in his book "The exposition of emotions in humans and animals", human emotions are biologically universal. This is being emphasized by the statement of psychologists that humans are universally able to produce emotions and recognize emotional expressions. However, from the perspective of cross-cultural anthropology, biological perspective itself is not enough, but it is necessary to take into account the cultural context in which emotions are experienced, raised, and felt [14], [15].

Basic emotion is a number of discrete emotions that differ from each other significantly [16]. Basic emotion differences are the result of an evolutionary process that shapes the functions and appearance of different emotions based on their basic tasks in life. Ekman defines six basic emotions types: happy, sad, angry, surprise, disgust, and fear. Psychologists also classify basic emotions into two classes; the class of positive emotions, and the class of negative emotions.

Meanwhile, mixed emotion is defined as affective experiences that have the characteristics of activating two or more basic emotions, usually the two emotions that have opposite valences such as pleasure and fear. Valence is a psychological term that indicates emotional characteristics, whether positive or negative. Another definition states that mixed emotions are an intra-individual correlation between opposite dimensions of affection (positive and negative), where the correlation value near zero means high emotional complexity [17]. This definition indicates that mixed emotions are experienced at different times (over the time) or there is a change in emotional state [18].

B. Facial Expression and Fuzzy Emotion

Emotion is an adaptation mechanism of organism to survive in their environment. Efforts to model human emotions have been carried out using various nonverbal signals, i.e. facial expressions, gestures, speech tones, and eye movements. One way to show emotions is through facial expressions. The problem is many variations of facial expressions that show human emotions. In addition, humans can subjectively express the same emotions in a variety of ways. This is the basic concept of fuzzy emotion term, regarding to the ambiguity and uncertainty of subjective human emotion.

Mixed emotions are expressed in a dimensional model whereas emotions cannot be separated in discrete categories but instead are arranged in a multidimensional continuously [19]. The continuous value of emotions indicates the degradation and intensity of emotions expressed and can vary in value in each emotion dimension. Fuzzy emotion is a generalization of mixed emotions that have intensity and able to describe various dimension of emotions that appear in a facial expression. Fuzzy emotion is a concept for translating ambiguous human natural emotions due to fuzzy perception.

Analysis of facial expressions to understand human behavior has become the focus of many studies in all relevant fields. There are thousands of facial muscle combinations that produce facial expressions [15]. In this study, facial expressions were captured through observation of facial components involved in the formation of facial expressions. Facial component analysis is done by observing the semantic features and facial linguistic features which will be explained in the next sub-section.

C. Image Representation

Image representation is a representation of image as a feature. High-level feature representation or semantic feature can use ontology to define high-level concepts of objects that are easily understood using human language by combining low-level features (color, position, size, and shape) to describe the linguistics of objects or regions in the image. Examples of linguistic features of objects are: sky is very blue, eyes open, mouth closes.

Semantic feature is a high-level feature which explain the object components, i.e. facial components are mouth, eyes, and nose. Machine learning defines the semantic feature by training some number of images so that the machine learning classifier can recognize the semantics of its category labels. This can be done with the Naïve Bayes algorithm, Support Vector Machine, Neural Network, and Decision Tree. There is also Relevance Feedback technique which involves the user's opinion in the process of determining semantic objects.

III. Fuzzy Emotion Recognition Framework

The proposed framework for fuzzy emotion recognition is depicted in the diagram in Fig. 1. The fuzzy emotion recognition framework consists of four main subsystems: 1) face point detection; 2) facial semantic feature extraction; 3) fuzzy facial component subsystem; 4) fuzzy emotion classification. Input is a static face image with single subject and frontal display, without occlusion is passing through the framework. Each image is then processed in the following ways:

- The face region is detected using the Active Appearance Methods (AAM) which produces an output of 68 facial points.
- Semantic feature extraction of facial components converts face points into facial components using geometric model analysis that produces output in the form of facial components (FC) parameters.
- The fuzzy facial component subsystem (FFC) produces a set of linguistic conditions of facial components which is treated as input for the fuzzy emotion classification subsystem.
- Fuzzy emotion inference system (FEIS) produces output in the form of the degree of fuzzy emotional values.

The preprocessing step is face detection. Face areas are detected using AAM which works fast in finding facial areas by marking facial points. AAM is a computer vision technique based on machine learning that works in a supervised manner. Initially, AAM learns from a face images dataset and creates a template reference that best match the face area. AAM detects the location of face fiducial points and give a label on it as Face Points (FP).

A. Fuzzy Facial Components

FP or facial points represent the location of face landmarks and are extracted using the geometric feature extraction techniques to produce sematic features. Only FPs which lie in the facial components involved in the formation of facial expressions, hence it makes the proposed method work efficiently.

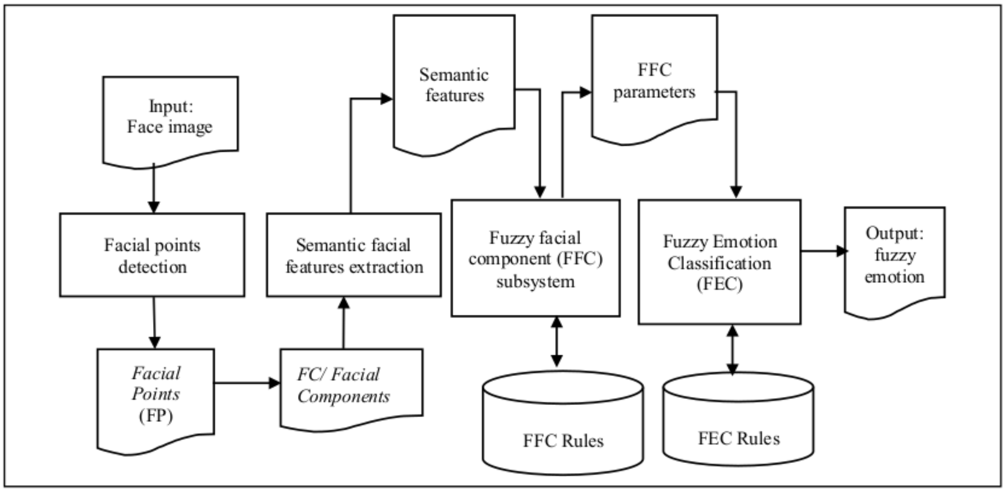


Fig. 1. The fuzzy emotion recognition framework

A set of semantic features was extracted from ten facial components, namely: left eyebrow and right eyebrow, inner eyebrow, left eye and right eye, nose, upper and lower lip, inner mouth and outer mouth. Inner brow is a meeting between the left eyebrow and the inner right eyebrow. The inner mouth is the elliptical area between the upper lip and the lower lip, while the outer mouth is the elliptical area around the lips.

All FP coordinate positions are recorded, but some FPs located in the jaw area are excluded in the feature extraction process because this FP does not produce rapid signals for semantic features. Semantic feature extraction processes each facial component separately. Unlike other studies, this subsystem does not use reference templates for semantic feature extraction.

Semantic features are captured based on geometric properties of facial components. Two types of geometric properties proposed in this study are elliptical eccentricity and distance ratio. The first feature comes from the idea that some facial components have elliptical or half elliptical shapes, namely the eyes, eyebrows, lips, and mouth. Semantic feature extraction uses elliptical eccentricity parameters as the first type of geometric properties. Eccentricity represents the level of elliptical curvature. This value ranges from zero to one, where zero values indicate a circle. The greater the value, the more elliptical the object. Elliptical eccentricity is related to the facial component semantic; i.e. eyes that are wide open or mouth wide open imply a small eccentricity, and vice versa. The second type of semantic feature is the distance ratio. It uses ratio because it does not depend on the unit of measurement and shows the comparison of the distance from the height or width of the facial components.

The next step is evaluating facial component rules. A set of rules has been stored in FFC inference engine. Rules are important in inferencing to calculate all possible input linguistic conditions in the antecedent section and to correlate them with the output in the consequent section based on the knowledge of the psychologist. FFC is based on Fuzzy Mamdani Inference System [20]. Defuzzification is applied to the output area using the centroid of gravity method. The result is a set of *yFCi* fuzzy facial component/FFC parameters. Furthermore, these FFC output parameters are becoming input of the next subsystem; fuzzy emotion classification. The linguistic features are defined on Table 1.

TABLE I. LINGUISTIC FEATURES OF FACIAL COMPONENTS

No	Semantic Features	Linguistic Features		
1	Left eyebrow	down	Normal	raise
2	Right eyebrow	down	Normal	raise
3	Inner eyebrow	closer	Normal	-
4	Left eye	narrow	Normal	wide
5	Right eye	narrow	Normal	wide
6	Nose	normal	wrinkled	-
7	Upper lip	thin	Normal	thick
8	Lower lip	thin	Normal	thick
9	Inner mouth	tight	Normal	open
10	Outer mouth	tight	Normal	open

Table 1 shows the semantic features or the FFC parameters which produced the linguistic features based on the value of the facial components.

B. Fuzzy Emotion Classification

In this study, there are six separate FECs each for a different basic emotion class. The six FECs are independent of each other. The reason behind the separation of emotions into six fuzzy emotion classifiers is because they do not lie in the same dimension or interval, so they cannot be forced to be placed into one output dimension since it is irrelevant. Each class of emotions has its own dimensions and intervals with different emotion intensities or fuzzy emotion degree.

FEC has three main processes: input fuzzification, fuzzy emotion inference, and output defuzzification. Ten FFC parameters from the previous subsystem are becoming input that passing through six FECs. The setting of FFC parameters for each fuzzy emotion classifier sourced from psychologists' expert knowledge [1], where Ekman has defined facial components involved in every type of basic emotion so that it can be used as a reference in the recognition of emotions.

Fuzzy emotion rules are developed from the knowledge of psychologists drawn from Ekman's theory [2], [3], as well as from observations and interviews with psychologists. Every FEC has different rules, i.e. 42 angry rules, 37 disgust rules, 69 fear rules, 73 happy rules, 47 sad rules, and 83 surprise rules. The number of rules is relevant to the number of FFC parameters. An example of FEC rule is: IF left and right eyebrow is normal AND left and right eye is narrow AND upper and lower lip is tight THEN fear is low.

Fuzzy emotion works by inferencing linguistic conditions from stored rules and producing fuzzy emotion values using Fuzzy Sugeno method [21]. All rules are then arranged and mapped into the solution in the output space. Output results consequently are inferred based on fuzzy rules that have been formed, where for each output ($z_1, z_2, z_3, \ldots, z_n$) is constant using the singleton membership function. Then defuzzification and normalization are performed to get the fuzzy value of each class of emotions located in the interval [0,1], using the weighted average sum defuzzification equation. The classifier works based on explainable AI principle which is as a rule-based classifier, each output is not a "black box" decision. It means that we can trace the linguistic features that defined one emotion. For example; angry is the result of inner eyebrow getting closer, upper and lower lip getting thinner, and eyes getting narrower.

IV. Experiments and Results

The experiment of facial expression recognition and fuzzy emotion required specific strategies that were arranged in a testing scenario. Emotion recognition testing based on fuzzy emotion concept was not compared to the existing emotion recognition methods based on the reason that existing emotion recognition methods, such as SVM, Neural Network, Deep Learning, and Fuzzy Clustering worked discretely to classify emotions into basic emotion classes. This was different from the concept of fuzzy emotion which recognized multi-dimensional emotions without eliminating any emotions contained in facial expressions. Whereas the classification of multi-dimensional emotions has never been proposed before. Therefore, the performance of emotion recognition based on the concept of fuzzy emotion cannot be compared with existing methods.

Experiment was done by dividing it into two main testing scenarios: 1) testing the FFC subsystem and; 2) testing the FEC subsystem. In the first scenario, testing was done to measure the performance of linguistic condition recognition of facial components, while in the second scenario testing is carried out to measure the performance of fuzzy emotion recognition as the final result of the proposed system. In each scenario, the dataset and validation from the expert to ensure the reliability of the dataset were needed. The facial expression datasets used were: 1) Extended Cohn Kanade (CK+) [22]; 2) Japanese Female Facial Expression (JAFFE) [23]; 3) Denver Intensity Spontaneous Facial Action (DISFA) [24]; and our custom-made 4) Indonesian Mixed Emotion Dataset (IMED) [25].

FFC subsystem testing was performed on the CK+ dataset to measure the performance of facial component recognition linguistic conditions. The test used 304 images from the CK+ dataset consisting of six basic emotion classes: 45 angry, 58 disgust, 25 fear, 72 happy, 23 sad, and 81 surprise. To measure the accuracy of the face component recognition results, we need a benchmark reference in the form of ground-truth data. Table 2 shows the result of the facial components recognition.

TABLE II. Facial Components recognition resjlts

FC	Accuracy	Precision	Recall	F1
Left eyebrow	0.987	0.988	0.985	0.986
Right eyebrow	0.990	0.995	0.984	0.989
Inner eyebrow	0.974	0.976	0.973	0.974
Left eye	0.970	0.967	0.977	0.972
Right eye	0.967	0.978	0.978	0.978
Nose	0.964	0.965	0.964	0.965
Upper lip	0.990	0.970	0.993	0.981
Lower lip	0.987	0.991	0.798	0.884
Inner mouth	0.967	0.979	0.865	0.918
Outer mouth	0.993	0.997	0.991	0.994
	0.979	**0.980**	**0.951**	**0.965**

Experiment in scenario one measured accuracy, precision, recall, and F1 score. FFC subsystem has a high average accuracy of 0.979, an average precision of 0.980, and an average recall of 0.951. The highest measurement accuracy is the outer mouth (0.993), the highest precision is also the outer mouth (0.997), and the highest recall is the upper lip (0.993). While the lowest accuracy is the nose (0.964%), the lowest precision is also nose (0.965), and the lowest recall is the lower lip (0.798).

In scenario 2, we observed the performance of fuzzy emotion recognition through experiments. Tests were carried out on four different facial expression datasets. The recognition results were accurate if the system properly captured fuzzy emotion; both in single and multiple values, which were then re-checked against the image label and the rating of the rater. The results were validated by 30 raters who had knowledge in fuzzy logic and emotion recognition, so the results were not claimed subjectively. In addition, the most dominant emotion intensity was used to determine the emotional categories of an image. Then, the results were compared with the emotion class labels on the four annotated datasets to calculate the accuracy of fuzzy emotion recognition. The results for fuzzy emotion recognition are shown in Fig. 2. The blue bars are the fuzzy emotion intensities for each class showing the most dominant emotion is surprise.

Fig. 2 Fuzzy emotion recognition result

TABLE III. AAM FACIAL POINTS DETECTION

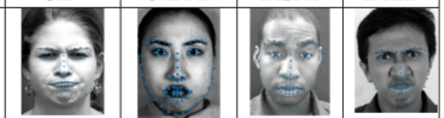
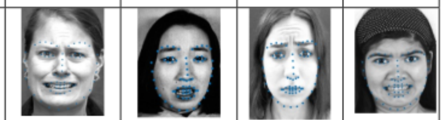
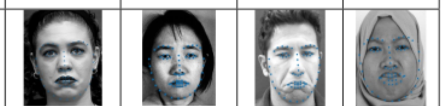
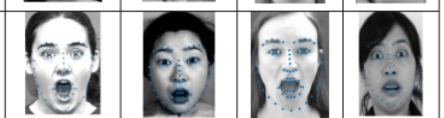
Emotion	Facial Expression Dataset
	CK+ / JAFFE / DISFA / IMED
Angry	
Disgust	
Fear	
Happy	
Sad	
Surprise	

Table 3 is the result of AAM detection using 4 datasets. The results of emotion recognition based on the fuzzy emotion concept using four different datasets are shown in Table 4.

TABLE IV. FUZZY EMOTION RECOGNITION RESJLT

Dataset	Accuracy rate						Avg. Accuracy
	Ang.	Dis.	Fear	Hap.	Sad	Sur.	
CK+	0.89	0.83	0.87	0.95	0.86	0.94	**0.90**
JAFFE	0.80	0.83	0.84	0.84	0.81	0.93	**0.82**
DISFA	0.85	0.93	0.92	0.91	0.86	0.92	**0.89**
IMED	0.84	0.87	0.87	0.87	0.89	0.89	**0.87**
	0.85	**0.87**	**0.87**	**0.89**	**0.85**	**0.92**	

Accuracy rate = 0.88±0.04

From Table 4, it can be seen that the performance of FEC varies from 0.80 to 0.95 (on a scale from 0 to 1). The average accuracy rate for all datasets is 0.88 with a standard deviation of 0.04. Surprise class obtained the highest average accuracy for all test data (0.92), while the lowest were angry and sad (0.85). Meanwhile, for different datasets, the highest average accuracy level is CK+ (0.90) and the lowest is JAFFE (0.82). In CK +, the highest introduction is happy class (0.95); in JAFFE the highest introduction is the surprise class (0.93); at the highest recognition DISFA is the disgust class (0.93); in IMED, the highest recognition is sad and surprise (0.89).

V. DISCUSSIONS

Based on the experiment results, it can be concluded that in a rule-based system, the value of precision can be high because the system is discriminatory and has specific rules. While the recall value tends to be low because of the inability of learning from data as in generative methods (machine learning). This is in line with the facts obtained from the test results in Table 2, where the recall value is lower than the precision and accuracy. The average F1 value is 0.965 which shows that there is a very strong relationship between precision and recall. This high value is achieved because geometric feature extraction has provided the best feature descriptor to the FFC subsystem. The knowledge-based engine of facial components from FFC also has an advantage in analyzing the linguistic conditions of facial components. The test results show that knowledge built from the rules of a psychologist is a determining factor in producing correct identification of the linguistic conditions of facial components. If the performance of facial component linguistic recognition subsystem is very good, it is expected that the fuzzy emotion recognition is also good because it gets input from the FFC. subsystem.

Fig. 3 shows a comparison chart of fuzzy emotion recognition using the CK +, JAFFE, DISFA, and IMED datasets.

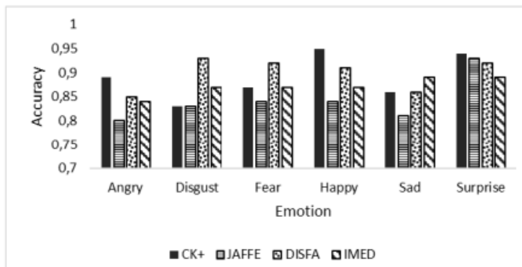


Fig. 3 The comparison of fuzzy emotion recognition

Horizontal and vertical axes indicate classes of emotion and level of accuracy. The chart in Fig. 3 can be observed by focusing on each category of emotions. Four different bars are four datasets. Aligned bars indicate that recognition performance has relatively the same accuracy for different datasets. For example, in the angry class, DISFA and IMED are almost equal; in the disgust class, CK+ and JAFFE are parallel; in the sad class, CK+ and DISFA are parallel; and in the surprise class, CK+ and JAFFE are parallel. The accuracy rate ranges from 0.8-0.95. Overall, it can be concluded that the performance of fuzzy emotion recognition performs well after being tested on the CK+, JAFFE, DISFA and IMED datasets.

VI. CONCLUSIONS

This study proposed fuzzy emotion recognition framework that works naturally to recognize human natural emotions and their intensities on the face image based on the knowledge of expert psychologists. Input in the form of facial expression images were processed using geometric feature extraction to get a higher representation of features; or semantic features and linguistic features of facial components. The output is a fuzzy emotion vector which has an element in the form of an intensity of multi-emotion values that appears simultaneously on a facial expression with a range of values [0,1]. The novelty of the fuzzy emotion recognition system is that it can capture mixed emotions in facial expression images, as well as determine the intensity of emotions that arise based on the linguistic conditions in facial components.

The facial component linguistic condition experiment gave very good results on the CK + dataset with an accuracy level of 0.98. Fuzzy emotion recognition experiments on four facial expression datasets showed a high performance with an average accuracy rate of 0.88, with the consecutive accuracy ratings were CK +, DISFA, IMED, and JAFFE. The highest level of accuracy is the CK + dataset which is 0.90. While the accuracy of the custom-made IMED dataset is 0.87. This accuracy is better than the accuracy of the JAFFE which is 0.82. This shows that the dataset built in this study has good validity so that the fuzzy emotion recognition system can recognize it well too. The system built can be widely used for various applications of human and computer interactions that require social intelligence, especially the recognition of emotions in various fields. The notable things are the fuzzy emotion recognition system only makes recognition based on facial expressions that are visually captured by the camera. This gives limitations to the results of emotional recognition because it does not involve cognitive appraisal factors, socio-cultural factors, and the context in which the emotions are experienced, raised, and felt.

Suggestions for future improvements are that increasing knowledge and perfecting fuzzy parameters is very important to achieve more accurate recognition results. Besides, improvement on the extraction of facial Points using AAM method needs to be improved. Fuzzy facial component analysis has the potential to be applied in other areas that take into consideration the linguistic condition of the face component in observation; such as pain detection, stress detection, lie detection. In addition, to improve system performance can be done by modifying image features, multimodal social signals, optimizing fuzzy parameters, and completing IMED metadata for better utilization.

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