# 특징점 기반의 적응적 얼굴 움직임 분석을 통한 표정 인식

## Feature-Oriented Adaptive Motion Analysis For Recognizing Facial Expression

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**Abstract** Facial expressions provide significant clues about one's emotional state; however, it always has been a great challenge for machine to recognize facial expressions effectively and reliably. In this paper, we report a method of feature-based adaptive motion energy analysis for recognizing facial expression. Our method optimizes the information gain heuristics of ID3 tree and introduces new approaches on (1) facial feature representation, (2) facial feature extraction, and (3) facial feature classification. We use minimal reasonable facial features, suggested by the information gain heuristics of ID3 tree, to represent the geometric face model. For the feature extraction, our method proceeds as follows. Features are first detected and then carefully "selected." Feature "selection" is finding the features with high variability for differentiating features with high variability from the ones with low variability, to effectively estimate the feature's motion pattern. For each facial feature, motion analysis is performed adaptively. That is, each facial feature's motion pattern (from the neutral face to the expressed face) is estimated based on its variability. After the feature extraction is done, the facial expression is classified using the ID3 tree (which is built from the 1728 possible facial expressions) and the test images from the JAFFE database. The proposed method excels and overcomes the problems aroused by previous methods. First of all, it is simple but effective. Our method effectively and reliably estimates the expressive facial features by differentiating features with high variability from the ones with low variability. Second, it is fast by avoiding complicated or time-consuming computations. Rather, it exploits few selected expressive features' motion energy values (acquired from intensity-based threshold). Lastly, our method gives reliable recognition rates with overall recognition rate of 77%. The effectiveness of the proposed method will be demonstrated from the experimental results.

*Keywords: facial expression, facial features, adaptive motion analysis, ID3 tree.*

## 1. Introduction

Facial expression is an important element in human communication and the studies have shown that facial expression reveals the underlying emotion of the human [5]. Since facial expression provides significant clues about one's emotional state, interests have been risen [1, 2, 9, 15] on human-computer interaction (HCI) of how machines can understand facial expressions of the human.

However, it always has been a great challenge to build a machine that recognizes human facial expressions effectively and reliably. The limitation of the automated machine for recognizing facial expressions is that complex human facial features are represented with "limited" verbal descriptions (i.e. any descriptions that can be described verbally) of facial expressions. We say "limited" because the human language may not describe every little details perceived by the human visual system. The best known facial expression analyzer i.e. the human visual system is "trained" by the tremendous amounts of data over the substantial time with the best known parallel learning system (i.e. the human neurons and their network), and it is safe to say that artificially reproducing the complex feature representation methods used by the human visual system is near impossible.

Previous researches have heavily relied on accurate estimates of facial feature movements on the face. They used facial expression representations based on Facial Action Coding System (FACS) [4, 6], 3D modeling of the human face [7], Gabor wavelet representation [1, 12, 13], or other geometric face model [8, 17] in an attempt to represent facial features as closely as possible to meet the verbal descriptions of human facial expressions. By considering many features, they may represent low-level details of the facial expression; however, they tend to be complicated and time-consuming to process.

In this paper, *feature-oriented adaptive motion analysis for recognizing facial expressions* is presented. Unlike previous efforts, our method is simple but effective. It avoids complicated and computationally expensive algorithms by using the information gain heuristics of ID3 tree [14]. ID3's information gain heuristics allows us to (1) define reasonably minimal features that are necessary to describe human facial expressions, and (2) selectively decide which features have high influences on classifying the emotion and perform motion orientation analysis on them. Based on ID3's information gain heuristics, we introduce new approaches for recognizing facial expression and they are: feature representation, feature selection, and adaptive motion analysis for the facial feature extraction, and rule-based classification using ID3 for the facial expression classification.

Our paper will be presented in the following order. In Section 2, ID3 Tree is introduced for the detailed explanation on the information gain heuristics of ID3. Then, Section 3 presents how we used this heuristics in our method to recognize facial expression. Then, Section 4 shows and discusses the experimental results and Section 5 draws the conclusion of this paper.

## 2. ID3 Tree

We used the ID3 tree throughout the proposed facial expression recognition method (not only in the facial expression classification but also in the facial feature representation and selection), and the mechanism of the algorithm is explained in this section.

### 2.1. ID3 - Introduction

ID3 tree [14] is a decision tree that operates based on ID3 algorithm. ID3 is based on the Concept Learning System (CLS) [20].

The basic CLS algorithm over a set of training instances $C$:

- Step 1: If all instances in $C$ are positive, then create YES node and halt; If all instances in $C$ are negative, create a No node and halt; Otherwise, Select a feature $F$ with values $V_1$, $V_2$, …, $V_n$ and create a decision node.
- Step 2: Partition the training instances in $C$ into subsets $C_1$, $C_2$, …, $C_n$ according to the values of $V$.
- Step 3: Apply the algorithm recursively to each of the sets $C_i$.

Note that the trainer (expert) decides which feature to select.

ID3 improves on CLS by adding a feature selection heuristic with the information gain i.e. entropy. ID3 searches for the attributes that best classify the training sets and it proceeds in the following order. ID3 terminate if the attribute perfectly classifies the training sets. Otherwise it recursively operates on the n partitioned subsets to get their "best" attribute where n is the number of possible values of an attribute. The question arises, "How does ID3 search the attribute that best classify the training sets?"

### 2.2. ID3 Entropy – Feature Selection Heuristics

ID3 uses the entropy, the statistical property that indicates the information gain, of all the attributes of the training sets to find the attribute that best classify the training sets by choosing the attribute with the highest information gain (i.e. information being the most useful for classification). Entropy is defined as follows.

Given an entire sample set $S$,

$$Entropy(S) = \sum_{i=1}^{c} -P(i)\log_2 P(i)$$

Where $P(i)$ is the probability of class $i$'s occurrence in $S$ and there are $C$ classes.

## 3. Methodology

For any facial expression analyzer, including the best known facial expression analyzer i.e. the human visual system, it should first perceive the face and then its appearance to guess the underlying emotion of the facial expression. Our method attempts to imitate the human visual system and thus it is composed of three steps: face detection, facial feature extraction, and facial expression classification. In this section, details of each step are covered and we introduce our approaches for recognizing facial expression. Our new approaches include: feature representation, feature selection, adaptive motion analysis for the facial feature extraction, and rule-based classification using ID3 tree for the facial expression classification.

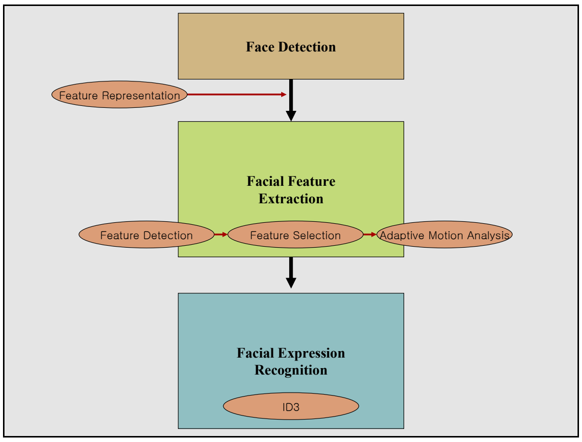



Figure1: Block Diagram of the proposed facial recognition method.

### 3.1. Face Detection

The first step to recognize the facial expression is detecting the human face, "Where is the face?" There have been various efforts on detecting the human face, namely face detection in facial images and in arbitrary images [15]. Although the static frontal-view facial images (i.e. images from JAFFE database) are dealt in the scope of this paper, we used the face detection method in arbitrary images for the future work of implementing the real-time system. Viola et al. [18] proposed the rapid object detection, including the human face, using a boosted cascade of simple features. Lienhart et al. [10] improved the performance by extending [18]'s rapid object detection framework. We adopted Lienhart's method into our system for the face detection.

### 3.2. Facial Feature Extraction

After the face is detected, the next step for the facial expression recognition is to extract facial expression information or facial features. In our approach, facial features are extracted in the following order. Predefined features are first detected and then carefully "selected" (by using the ID3 entropy, or information gain, of the feature), for differentiating features with high variability from the ones with low variability, to effectively calculate the motion energies. For each facial feature, adaptive motion analysis is performed. In the sections 3.2.1 through 3.2.4, feature representation as well as how the system is trained, feature detection, feature selection, and adaptive motion analysis on features are discussed in detail.

#### 3.2.1. Facial Feature Representation

One of the most critical issues in the automatic facial expression recognition is the representation of features, "Which features are used to represent the geometric face model and to classify the facial expression?" and "How are we going to represent these features?" The human visual system is "trained" by the tremendous amounts of data over the substantial time with the best known parallel learning system (i.e. the human neurons and their network), and it is safe to say that artificially reproducing the complex feature representation methods used by the human visual system is near impossible.

The limitation of the automated system for recognizing the facial expressions is that the features are represented with "limited" verbal descriptions (i.e. any descriptions that can be described verbally) of the facial expressions. We say "limited" because the language itself may not describe every little details perceived by the human visual system. The facial expression representations based on Facial Action Coding System (FACS) [4, 6], 3D modeling of the human face [7], Gabor wavelet representation [1, 12, 13], or other geometric face model [8, 17] attempt to represent facial features as closely as possible to meet the verbal descriptions of human facial expressions. By considering many features, they may represent low-level details of the facial expression; however, they tend to be complicated and time-consuming to process.

Based on the verbal descriptions of the facial expressions from DataFace [5, 19], our approach used 9 facial features to represent the geometric model of the face and classify the 6 emotional facial expressions. We first considered initial 15 features for the face model. 10,368 possible facial expressions, which are automatically generated based on the verbal descriptions of the expressions, are used for the initial training of the initial ID3 tree, and the initial ID3 tree is generated.

The subsequent result, i.e. initial ID3 tree, indicated that some features tend to move together (ex. left eyebrows and right eyebrows) and thus these features are united as one feature (ex. eyebrows for left eyebrows and right eyebrows) for the sake of reducing the complexity. ID3 is well-suited for this task because it searches for the attributes (i.e. features) that best classify the data (i.e. the emotion) and finds "unnecessary" features that may be discarded. After the removal of "unnecessary" features, the final of 9 features are used to represent the geometric model of the face and classify the 6 emotional facial expressions. Using the final 9 features and their "actions," 1728 possible facial expressions (that are obtained by considering every possible actions of each feature) are used to train the final ID3 tree for classifying the facial expression.

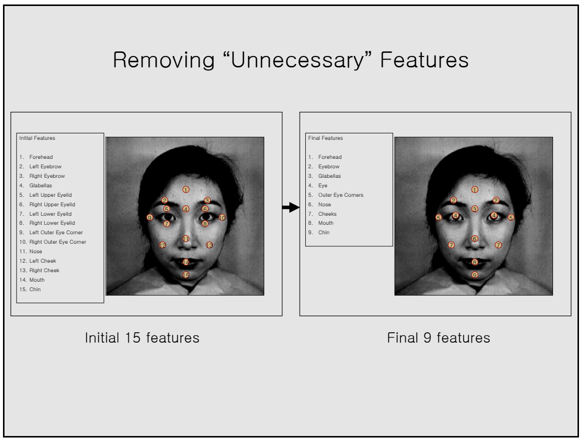



Figure2: For the facial expression analysis, the final of 9 features are obtained from the initial 15 features.

### 3.2.2. Facial Feature Detection

Based on the feature representations described in 3.2.1, 9 facial features are considered in our method of facial feature extraction. The foremost step for the feature extraction is detecting the facial features. We have adopted the feature detection framework done by Park et al [16] and modified it to detect more facial features.

The feature detection proceeds as follows:

(1) Once the face is detected, detected face region is rescaled into a 100-by-100 image. The resolution and sample density of the source image is reduced to restrict the search regions of the scene where facial features are most likely to occur.

(2) The valley image [3] of rescaled image is obtained since it can clearly show main features (features around the valley regions such as eyes, nose, and mouth) and thus easy detection of main features is possible. However, the information obtained from the valley image alone may require come computational expenses to detect the features. Thus, a generic feature template [11], which segment the rescaled face image into sub-regions for the main features (ex. R1 for right eye, R2 for left eye, R3 for nose, and R4 for mouth), is applied on the valley image for even more search region restrictions and the main facial features are detected in extremely fast and effective manner.

(3) After the main features are detected, remaining features are detected based on the locations of the “main” facial features.

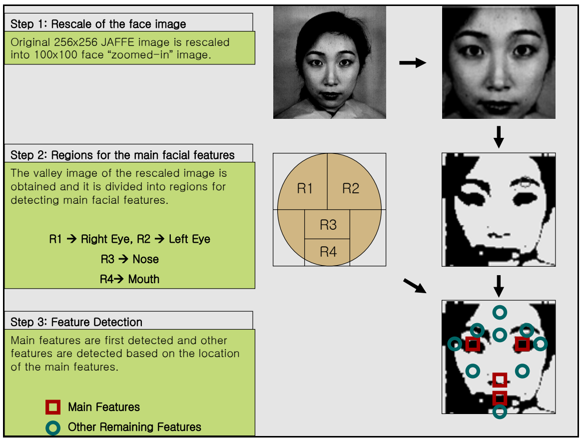



Figure 3: Feature Detection.

### 3.2.3. Facial Feature Selection

In our approach, each feature has two basic action states, neutral and expressed states, and expressed states are further categorized into sub-action states accordingly depending on features. Features and their “actions units” are shown in the table.

Table 1: “Action Units” of the final 9 features

| Features | Actions |
|---|---|
| 1. Forehead | - Neutral<br>- Expressed |
| 2. Eyebrow | - Neutral<br>- Up<br>- Down |
| 3. Glabellas | - Neutral<br>- Expressed |
| 4. Eye | - Neutral<br>- Narrowed<br>- Widened |
| 5. Outer Eye Corners | - Neutral<br>- Expressed |
| 6. Nose | - Neutral<br>- Expressed |
| 7. Cheeks | - Neutral<br>- Expressed |
| 8. Mouth | - Neutral<br>- Open Wide<br>- Thinned<br>- Upper Lip Drawn up<br>- Lip Corners Up<br>- Lip Corners Down |
| 9. Chin | - Neutral<br>- Expressed |

Each feature’s actions, obtained from the verbal descriptions of the feature, show the variability of the feature (i.e. the motion energy orientation of the feature). They are used to differentiate the features with high variability from the ones with low variability, and by doing so we can effectively analyze the changes in motion by performing the adaptive motion analysis. Adaptive motion analysis is performing the orientation evaluation on selected features. That is, the features with one expressed states (for example, features with low variability such as forehead, cheek, etc.) are excluded from the orientation evaluation, and only the features with more than one expressed states (for example, features with high variability such as mouth, eyebrows, eye, etc.) are evaluated for their orientations.

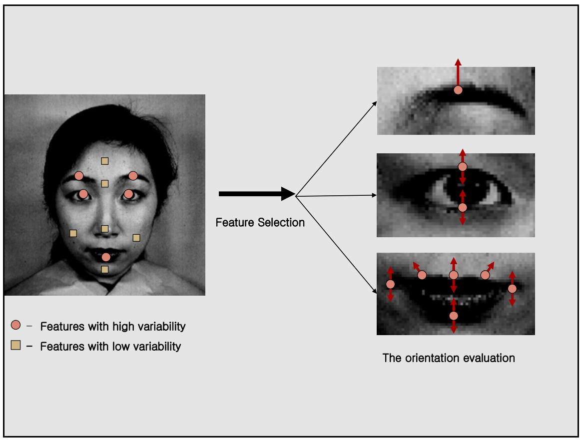



Figure4: Feature Selection.

### 3.2.4. Adaptive Motion Analysis on Features

Adaptive motion analysis is to effectively capture the patterns (namely the intensity and the orientation) of the features from the neutral face image to the expressed face image. Park et al [16] proposed the point-wise motion analysis (i.e. motion analysis is done by specifying the rectangle region on each facial features) for facial expression recognition, but their work is only concerned with the intensity of the features (i.e. "Was there an 'action' from the neutral face image to the expressed face image?").

#### 3.2.4.1. Our Approach

Our approach extended [16]'s motion analysis framework in two ways. First, we consider not only the intensity of features but also the orientation of the features. Orientation of the feature can be thought as detailed information of the feature intensity, and in our approach the orientation of the feature is described by the expressed states as explained in Section 3.2.3. Second, we apply the adaptive motion analysis on the facial features. That is, the orientation evaluation is performed only on selected features and the intensity evaluation is performed on non-selected features.

#### 3.2.4.2. Orientation Evaluation

The orientation evaluation is performed by pattern tracking. Pattern tracking is similar to feature tracking in a sense that patterns are first located in each image frame, then the patterns are followed from frame to frame to estimate motion [21]. We extended the pattern tracking method proposed by Park et al [16]. Two images, neutral and expressed face images, are used to estimate the motion of the features by finding the "difference image." The "difference image" is the image of difference in patterns from the neutral to the expressed image, and it represents the motion of the facial expression.

For each selected facial feature, a rectangle box is first specified for the calculation of the feature's motion. In order to evaluate the feature's orientation, the original rectangle box is divided into a number of small sub-rectangle boxes (number of small sub-rectangle boxes is closely tied to the number of expressed states of the feature), then we calculate the motion energy values for each of them, and finally the motion energy values for each sub-rectangle box is compared to determine the feature's orientation.

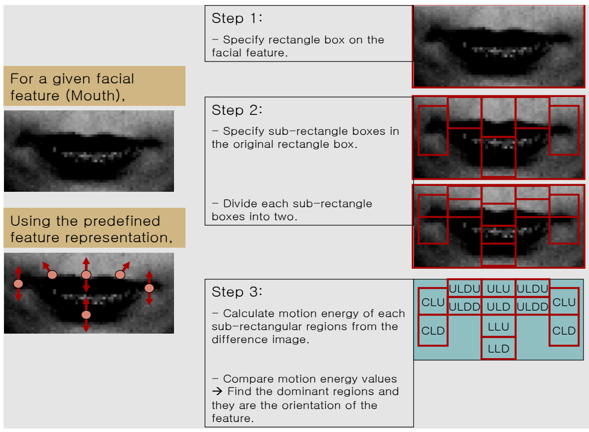



Figure5: Orientation Evaluation.

### 3.3. Facial Expression Classification

Once the facial features are extracted and they are represented as attributes (i.e. discrete attributes that describes the facial expression), ID3 tree can be used to classify the given facial expression.

### 3.3.1. ID3 requirements for the test data

ID3 algorithm has requirements (or limitations) on the sample data it can take [20], and in this section, these requirements are examined to see if our ID3 tree is suited for the facial expression recognition.

There are four requirements that the sample data used in ID3 algorithm must follow: (1) the same attributes must describe each example and have a fixed number of values. (2) An example's attributes must already be defined, i.e. they are not learned by ID3. (3) Discrete classes should be used and classes broken up into vague categories are not good. (4) There must be sufficient training examples to distinguish valid patterns from chance occurrences.

We have met all the requirements since our ID3 tree is trained with the total of 1728 possible facial expressions (satisfy 4th condition) that are generated based on 9 predefined (satisfy 2nd condition) facial features with a fixed number of actions (satisfy 1st condition). Furthermore, the "unnecessary" features from the initial 15 facial features are removed to use only the discrete facial features (satisfy 3rd condition), and the final of 9 facial features are considered to represent the face model and to generate the sample data.

### 3.3.2. ID3 tree for the classification

Our classification is based on rule-based method, and the ID3 decision tree is used since our ID3 tree and the training data meets the requirements imposed by ID3 algorithm. Unlike previous efforts on statistically comparing and classifying the facial expressions that are complex, computationally expensive, and time-consuming, our classification method using ID3 decision tree is based on simple Boolean comparisons. Moreover the entropy or the information gain of ID3 algorithm searches for the facial features that best classify the facial expression, and thus it forces the classification system to recognize the facial expression with minimal comparison steps.

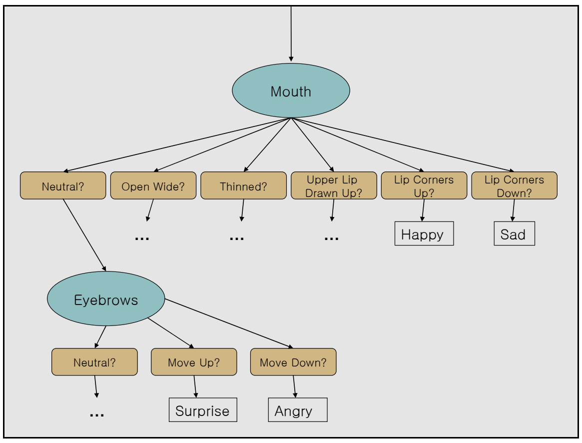



Figure6: ID3 Tree for the facial expression recognition.

As you can see from the above figure, mouth has the highest information gain in our ID3 tree and it is the first feature that the classification system will examine once the test data comes.

## 4. Experimental Results and Discussion

### 4.1. Experimental Results

We have tested the system on JAFFE (Japanese Female Facial Expression) database for quantitative analysis on 6 emotional states (Surprise, Disgust, Fear, Anger, Happiness, and Sadness).

95 Sample test images (Surprise: 17, Disgust: 14, Fear: 13, Anger: 14, Happiness: 21, and Sadness: 16) out of total of 192 images in the JAFFE database were used to test the system. The performance was pretty good and consistent with overall recognition accuracy of 77.6% (Surprise: 85.1%, Disgust: 77.1%, Fear: 69.6%, Anger: 82.3%, Happiness: 79.3%, and Sadness: 72.3%).

### 4.2. Discussion

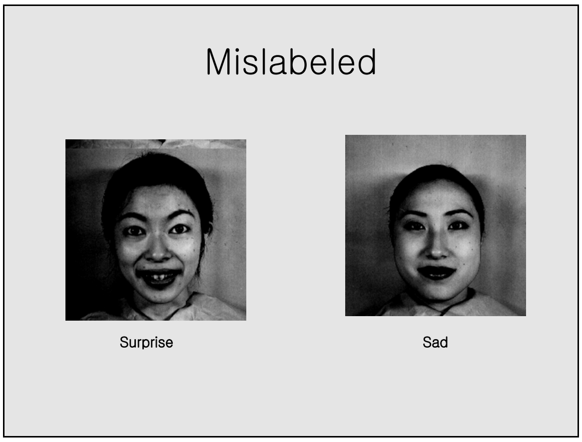
We first compare the performance of our method with other rule-based facial expression classification system that was tested on the JAFFE database, namely point-wise motion energy analysis implemented by Park et al [16].

Table 2: Comparison of our method with other rule-based method

| Methods | Scope | Database | Recognition Rate (%) |
|---|---|---|---|
| Point-Wise Motion Energy Analysis by Park et al [16]. | Pattern Tracking on Motion intensity of the feature | JAFFE | Overall: 70% (Fear: 64%, Sad: 70%) |
| Our Feature-Based Adaptive Motion Analysis | Pattern Tracking on Motion orientation as well as Motion intensity of the feature | JAFFE | Overall: 77% (Fear: 69%, Sad 72%) |

As you can see from the table, our method of tracking feature's motion orientation patterns performs better than [16]'s method of tracking feature's motion intensity patterns only. This indicates, as expected, that the facial feature orientation is the important element for recognizing facial expressions that should not be discarded.

It should be noted that there are "bad" samples, in the JAFFE database, that are prone to misclassify the facial expression. Certainly, we have taken into the consideration that facial expressions vary from one individual to another and the good classifier should handle well whether the sample is occurred by a chance or not. Our method handled quite well on "bad" samples. "Bad" samples can be categorized into two classes: "wrong" facial expressions that are mislabeled, and "weak" facial expressions that are misleading and hard to clearly classify so that even the human visual system may be puzzled. The examples of "wrong" facial expressions and "weak" facial expressions are shown below.




(a)


(b)

Figure7: Example of "bad," (a) mislabeled and (b) misleading, samples in JAFFE.

When there are significant amount of "bad" samples, it may inevitably affect the recognition rate of facial expressions. In the JAFFE database, "weak" expressions tend to be distributed heavily over facial expressions labeled as fear or sad and thus the recognition rate for fear and sad expressions were relatively low compared with other recognition rate. [16]'s experimental results also support our position.

## 5. Conclusion

In this paper, we have presented a simple, fast, and effective feature-based adaptive motion energy analysis method for recognizing facial expressions.

Our method optimizes the information gain heuristics of ID3 tree, and introduced three new approaches on: (1) facial feature representation (minimal reasonable facial feature representation for the geometric model of human face), (2) facial feature extraction (feature selection and adaptive motion analysis on features), (3) rule-based facial expression classification using ID3 tree. By using the minimal reasonable facial feature representation for the geometric model of human face, our method is simple and computationally inexpensive. Feature selection and adaptive motion analysis on features effectively estimate the feature's motion patterns from the neutral face to the expressed face. Moreover, the information gain of ID3 tree forces the facial expression classification to be done with minimal Boolean comparisons.

Our method performed quite well with 77% overall accuracy of recognizing facial expressions (Surprise, Fear, Disgust, Anger, Sad, and Happy). Our experimental result shows that the facial feature orientation plays an important role along with the facial feature intensity for recognizing facial expressions, and the valuable future research includes, but not limited to, a simple rule-based facial expression classification system that has a strong tolerance to "bad" data samples.

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