ABSTRACT: Emotion recognition is very important for human-computer intelligent interaction. It is generally performed on facial or audio information by artificial neural network, fuzzy set, support vector machine, hidden Markov model, and so forth. Although some progress has already been made in emotion recognition, several unsolved issues still exist. For example, it is still an open problem which features are the most important for emotion recognition. Feature selection for facial emotion recognition is studied based on rough set theory. A self-learning attribute reduction algorithm is proposed based on rough set and domain oriented data-driven data mining theory. It is found that the features concerning mouth are the most important ones in geometrical features for facial emotion recognition. It consists of 3 modules:

1. Feature selection for emotion recognition based on RST.
2. Facial action coding system (FAP).
3. Features concerning mouth.

1.1 BACKGROUND

Emotion recognition is very important for human-computer intelligent interaction. It is generally performed on facial or audio information by artificial neural network, fuzzy set, support vector machine, hidden Markov model, and so forth. Although some progress has already been made in emotion recognition, several unsolved issues still exist. For example, it is still an open problem which features are the most important for emotion recognition.

There have been several research works related to the important features for emotion in cognitive psychology. Based on the results of psychological experiments, the information conveyed by different facial parts has diverse effects on the facial expression recognition, and the eyes play the most important role. Some said that the low spatial frequency information is important for emotion, edge-based facial information is used for expression recognition.
1.2 NEED

In previous works of emotion recognition, attribute reduction algorithms based on classical rough set are used for the purpose of facial emotional feature selection, and SVM is taken as the classifiers. Some useful features concerning eyes and mouth are found. Based on these features, high correct recognition rates are achieved. However, classical rough set theory is based on equivalence relation. There must be a process of discretization in equivalence relation since the measured facial features are continuous values. Information might be lost or changed in the discretization process, thereby affecting the result. To solve this problem, some research works have been taken. Shang et al. proposed a new attribute algorithm, which integrates the discretion and reduction using information entropy-based uncertainty measures and evolutionary computation.

Ensen and Shen proposed a fuzzy-rough attribute reduction algorithm and an attribute reduction algorithm based on tolerance relation. Although these research works can avoid the discretization process, the parameters in these methods should be given according to prior experience of domain experts, for example, the fuzzy set membership function in Jensen’s fuzzy-rough attribute reduction algorithm, the population amount for Shang’s method. If there is no experience of domain experts, these methods will be useless in some extent. In this project, a novel feature selection method based on tolerance relation is proposed, which can avoid the process of discretization. Meantime, based on the idea of domain-oriented data-driven data mining (3DM), a method for finding suitable threshold of tolerance relation is introduced. Experimental results show that important and useful features for emotion recognition can be identified by the proposed method with a high recognition rate. It is found that the features concerning mouth are the most important ones in eometrical features for facial emotion recognition.

2. FEATURE SELECTION BASED ON ROUGH SET THEORY
2.1 ROUGH SET THEORY

Rough set (RS) is a valid mathematical theory for dealing with imprecise, uncertain, and vague information; it was developed by Professor Pawlak in 1980s. RS has been successfully used in many domains such as machine learning, pattern recognition, intelligent data analyzing, and control algorithm acquiring. The most advantage of RS is its great ability of attribute reduction (knowledge reduction, feature selection).

**Definition 2.1.** A decision information system is defined as a quadruple \( S = (U, C \sqcup D, V, f) \) where \( U \) is a finite set of objects, \( C \) is the condition attribute set, and \( D = \{d\} \) is the decision attribute set. For all \( c \in C \), with every attribute \( a \in C \sqcup D \), a set of its values \( V_a \) is associated. Each attribute \( a \) determines a function \( f_a : U \rightarrow V_a \).

**Definition 2.2.** For a subset of attributes \( B \sqsubseteq A \), an indiscernibility relation is defined by \( \text{Ind}(B) = \{(x, y) \in U \times U : a \in B, (ax = ay)\} \), in which \( ax \) and \( ay \) are values of the attribute \( a \) of \( x \) and \( y \).

The indiscernibility relation defined in this way is an equivalence relation. Obviously, \( \text{Ind}(B) = \bigcap b \in B \text{Ind} \{ \{b\} \} \) By \( U/\text{Ind}(B) \) we mean the set of all equivalence classes in the relation \( \text{Ind}(B) \). The classical rough set theory is based on an observation that objects may be indiscernible due to limited available information, and the indiscernibility relation defined in this way is an equivalence relation indeed. The intuition behind the notion of an indiscernibility relation is that selecting a set of attributes \( B \sqsubseteq A \) effectively defines a partition of the universe into sets of objects that cannot be discerned using the attributes in \( B \) only. The equivalence classes \( E_i \sqsubseteq U/\text{Ind} \_B \_ \), induced by a set of attributes \( B \sqsubseteq A \), are referred to as object classes or simply classes. The classes resulted from \( \text{Ind}(A) \) and \( \text{Ind}(D) \) are called condition classes and decision classes, respectively.

**Definition 2.3.** A decision information system is a continuous value information system, and it is defined as a quadruple \( s = (U, C \sqcup D, V, f) \), where \( U \) is a finite set of objects, \( C \) is the condition attribute set, and \( D = \{d\} \) is the decision attribute set. For all \( c \in C \), \( c \) is continuous value attribute.

A facial expression information system is a continuous value information system according to Definition 2.3. If a condition attribute value is a continuous value, indiscernibility relation cannot be used directly since it requires that the condition attribute values of two different samples are equal, which is difficult to satisfy. Consequently, a
process of discretization must be taken, in which information may be lost or changed. The result of attribute reduction would be affected. Since all measured facial attributes are continuous value and imprecise to some extent, the process of discretization may affect the result of emotion recognition. We argue that it is suitable for the continuous value information systems that the attribute values are taken as equal if they are similar in some range. Based on this idea, a method based on tolerance relation that avoids the process of discretization is proposed in this project.

**Definition 2.4.** A binary relation \( R = (x, y) \) defined on an attribute set \( B \) is called a tolerance relation if it satisfies

1. symmetrical: \( \forall x, y \in (R(x, y)) \Rightarrow R(y, x) \);
2. reflexive: \( \forall x \in \mathbb{U} (R(x, x) = 1) \).

From the standpoint of a continuous value information system, a relation could be set up for a continuous value information system as follows.

**Definition 2.5.** Let an information system \( S = (U, C \sqcap D, V, f) \) be a continuous value information system; a relation \( R(x, y) \) is defined as

\[
R(x, y) = \{(x, y) | x \sqcap \mathbb{U} y \sqcap \mathbb{U} a \sqcap C | ax - ay| \leq \varepsilon, 0 \leq \varepsilon \leq 1 \}
\]

Apparently, \( R(x, y) \) is a tolerance relation according to Definition 2.4 since \( R(x, y) \) is symmetrical and reflexive. In classical rough set theory, an equivalence relation constitutes a partition of \( U \), but a tolerance relation constitutes a cover of \( U \), and equivalence relation is a particular type of tolerance relation.

### 2.2. Feature Selection Based on Rough Set Theory and Domain-Oriented Data-Driven Data Mining

In this section, a novel attribute reduction algorithm is proposed based on rough set theory and domain-oriented data-driven data mining (3DM). 3DM is a data mining theory proposed by Wang 18, 19. According to the theory, knowledge could be expressed in different ways; that is, some relationship exists between the different formats of the same knowledge. In order to keep the knowledge unchanged in a data mining process, the properties of the knowledge should remain unchanged during the knowledge transformation process. Otherwise, mistake may occur in the process of knowledge transformation. Based on
this understanding, knowledge reduction can be seen as a process of knowledge transformation, in which properties of the knowledge should be remained.

In the application of emotion recognition, no faces are entirely the same nor are emotions. For any two different emotion samples, there must be some different features in the samples. Accordingly, an emotion sample belongs to an emotion state according to its features which are different to the others. From this standpoint, we argue that the discernability of the condition attribute set with respect to the decision attribute set can be taken as an important property of knowledge in the course of knowledge acquisition in emotion recognition. Based on the idea of 3DM, the discernability should be unchanged in the process of knowledge acquisition and attribute reduction.

**Definition 2.6.** Let $S = (U, C \square D, V, f)$ be a continuous value information system. If $\not\exists xi, xj \in U \neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg\neg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3. ATTRIBUTE REDUCTION FOR EMOTION RECOGNITION

The discernability of condition attribute set with respect to decision attribute set in tolerance relation is a fundamental feature of knowledge of a continuous value information
system. The discernability should be unchanged according to 3DM. Since $E_D|C_\_ 0$ is a necessary and sufficient condition for keeping the discernability of condition attribute set with respect to decision attribute set in tolerance relation, therefore, a self-learning attribute reduction algorithm _SARA_ is proposed for continuous value information systems as follows.

**Algorithm : Self-learning attribute reduction algorithm (SARA).**

**Input:** a decision table $S _ _ U, C \square D, V, f _ _$ of a continuous information system, where $U$ is a finite set of objects, $C$ is the condition attribute set, and $D \{d\}$ is the decision attribute set.

**Output:** a relative reduction $B$ of $S$.

**Step 1.** Compute $\epsilon_{opt}$, then set up a tolerance relation on the condition attribute set $C$.

**Step 2.** Compute condition entropy $E_D|C_\_$. 

**Step 3.** For all $a_i \square C$, compute $E_D|\{a_i\}_$. Sort $a_i$ according to $E_D|\{a_i\}_$ descendant.

**Step 4.** Let $B _ C$, deal with each $a_i$ as in the following.

**Substep 4.1**
Compute $E_D|B - \{a_i\}_$.

**Substep 4.2**
If $E_D|C_\_ E_D|B - \{a_i\}_$, attribute $a_i$ should be reduced, and $B _ B - \{a_i\}$, otherwise, $a_i$ could not be reduced, and $B$ is holding.

<table>
<thead>
<tr>
<th>Dataset name</th>
<th>Samples</th>
<th>People</th>
<th>Emotion classes</th>
</tr>
</thead>
<tbody>
<tr>
<td>CKACFE</td>
<td>405</td>
<td>97</td>
<td>Happiness, sadness, surprise, anger, disgust, fear, neutral</td>
</tr>
<tr>
<td>JAFFE</td>
<td>213</td>
<td>10</td>
<td>Happiness, sadness, surprise, anger, disgust, fear, neutral</td>
</tr>
<tr>
<td>CQUPTTE</td>
<td>652</td>
<td>8</td>
<td>Happiness, sadness, surprise, anger, disgust, fear, neutral</td>
</tr>
</tbody>
</table>
4. Experiment Results and Discussion

Since there are few open facial emotional dataset, three facial emotional datasets are used in the experiments. The first dataset comes from the Cohn-Kanade AU-Coded Facial Expression CKACFE database and the dataset is more representative of Caucasian to some extent. The second one is the Japanese female facial expression JAFFEdatabase and it is more representative of Asian women. The third one named CQUPTE is collected from 8 graduate students in the Chongqing University of Posts and Communications in China, in which there are four females and four males. Details of the datasets are listed in Table 1. Some samples are shown in Figure 1. In each dataset, the samples are happiness, sadness, fear, disgust, surprise, and angry from left to right in Figure 1. Facial expression of human being is expressed by the shape and position of facial components such as eyebrows, eyes, mouth, and nose. The geometric features, appearance features, wavelet features, and mixture features of facial are popular for emotion recognition in recent years. The geometric facial features represent the shape and locations of facial. Facial expression of human being is expressed by the shape and position of facial components such as eyebrows, eyes, mouth, and nose. The geometric features, appearance features, wavelet features, and mixture features of facial are popular for emotion recognition in recent years.
The geometric facial features represent the shape and locations of facial components, and it is used in the experiments since it is obvious and intuitionistic for the facial expression. The geometric facial features are the distance between two different feature points which are according to a defined criterion. The MPEG-4 standard is a popular standard for feature point selection. It extends facial action coding system _FACS_ to derive facial definition parameters _FDP_ and facial animation parameters _FAP_. There are 68 FAP parameters, in which 66 low parameters are defined according to FDP parameters to describe the motion of a human face. The FDP and low-level FAP can constitute a concise representation of a face, and they are adequate for basic emotion recognition because of the varieties of expressive parameter. In the experiments, 52 low FAP parameters are chosen to represent emotion because some FAP parameters have little effect on facialexpression. For example, the FAP parameter named raise l ear, which denotes the vertical displacement of left ear. Thus, a feature point set including 52 feature points is defined as shown in Figure 3. Based on the feature points, 33 facial features are extracted for emotion recognition according to listed in Table 2. The 33 facial features can be divided into three groups. There are 17 features in the first group which concern eyes and consists of \( d_0, d_1, d_2, d_3, d_4, d_5, d_6, d_7, d_16, d_17, d_19, d_{20}, d_{25}, d_{26}, d_{27}, d_{28}, \) and \( d_{29} \); there are 6 features in the second group which concern cheek and consists of \( d_9, d_{10}, d_{18}, d_{21}, d_{30}, \) and \( d_{31} \); there are 10 features in the third group.
which concern mouth and consists of $d_8, d_{11}, d_{12}, d_{13}, d_{14}, d_{15}, d_{22}, d_{23}, d_{24}$ and $d_{32}$. In Table 1, A is the midpoint of point 19 and 23, and B is the midpoint of point 27 and 31. $\text{dis}_{i,j}$ denotes the Euclid distance between point $i$ and $j$; $\text{hei}_{i,j}$ denotes the horizontal distance between point $i$ and $j$; $\text{wid}_{i,j}$ denotes the vertical distance between $i$ and $j$. Since the distance between point 23 and 27 is stable for all kinds of expression, we normalize the distance features in the following way.

Firstly, $x'_i = \frac{x_i - \min(x_i)}{\max(x_i) - \min(x_i)}$, $x_i \in [0, 1]$.

<table>
<thead>
<tr>
<th>feature</th>
<th>description</th>
<th>feature</th>
<th>description</th>
<th>feature</th>
<th>description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$d_0$</td>
<td>dis(11, 19)</td>
<td>$d_{11}$</td>
<td>dis(39, 44)</td>
<td>$d_{22}$</td>
<td>dis(44, 48)/2</td>
</tr>
<tr>
<td>$d_1$</td>
<td>dis(18, 31)</td>
<td>$d_{12}$</td>
<td>dis(39, 48)</td>
<td>$d_{23}$</td>
<td>dis(45, 51)</td>
</tr>
<tr>
<td>$d_2$</td>
<td>dis(21, 25)</td>
<td>$d_{13}$</td>
<td>dis(44, 48)</td>
<td>$d_{24}$</td>
<td>dis(47, 49)</td>
</tr>
<tr>
<td>$d_3$</td>
<td>dis(20, 26)</td>
<td>$d_{14}$</td>
<td>dis(46, 50)</td>
<td>$d_{25}$</td>
<td>dis(14, 23)</td>
</tr>
<tr>
<td>$d_4$</td>
<td>dis(22, 24)</td>
<td>$d_{15}$</td>
<td>dis(30, 3)</td>
<td>$d_{26}$</td>
<td>dis(15, 27)</td>
</tr>
<tr>
<td>$d_5$</td>
<td>dis(29, 33)</td>
<td>$d_{16}$</td>
<td>dis(21, A)</td>
<td>$d_{27}$</td>
<td>dis(19, 23)/2</td>
</tr>
<tr>
<td>$d_6$</td>
<td>dis(28, 34)</td>
<td>$d_{17}$</td>
<td>dis(A, 25)</td>
<td>$d_{28}$</td>
<td>dis(27, 31)/2</td>
</tr>
<tr>
<td>$d_7$</td>
<td>dis(30, 32)</td>
<td>$d_{18}$</td>
<td>hei(A, 44)</td>
<td>$d_{29}$</td>
<td>(wid(19, 23) + wid(27, 31))/2</td>
</tr>
<tr>
<td>$d_8$</td>
<td>dis(39, 46)</td>
<td>$d_{19}$</td>
<td>dis(29, B)</td>
<td>$d_{30}$</td>
<td>(hei(11, 39) + hei(18, 39))/2</td>
</tr>
<tr>
<td>$d_9$</td>
<td>dis(23, 44)</td>
<td>$d_{20}$</td>
<td>dis(B, 33)</td>
<td>$d_{31}$</td>
<td>(hei(14, 39) + hei(15, 39))/2</td>
</tr>
<tr>
<td>$d_{10}$</td>
<td>dis(27, 48)</td>
<td>$d_{21}$</td>
<td>hei(B, 48)</td>
<td>$d_{32}$</td>
<td>(hei(44, 39) + hei(48, 39))/2</td>
</tr>
</tbody>
</table>

3.1. Experiments for the Features Concerning Mouth for Emotion Recognition

From the last section, we draw a conclusion that the geometrical features concerning mouth are important for emotion recognition. In this section, there are four experiments for the purpose of testing the importance of the geometrical feature concerning mouth for emotion recognition. In the first experiment, all the 33 facial features are used for emotion recognition. In the second experiment, only the features selected by SARA are used for a
a) Common features by SARA

b) Common features selected by CEBARKNC
c) Common Features selected by MIBARK

FIG3: Common Features

emotion recognition. In the third experiment, all the features concerning mouth are deleted, and there are 19 features that are used for emotion recognition, in which there are 17 features concerning eyes $d_0, d_1, d_2, d_3, d_4, d_5, d_6, d_7, d_{16}, d_{17}, d_{19}, d_{20}, d_{25}, d_{26}, d_{27}, d_{28}, d_{29}$, and two features $d_{30}, d_{31}$ concerning cheek but not mouth. In the fourth experiment, all the features concerning eyes are deleted, and there are 12 features that are used for emotion recognition, in which there are 10 features concerning mouth $d_8, d_{11}, d_{12}, d_{13}, d_{14}, d_{15}, d_{22}, d_{23}, d_{24}, d_{32}$, and two features $d_{30}, d_{31}$ concerning cheek but not eyes. SVM is taken as classifier in the four experiments and is given the same parameters. Experiment results are listed in Table3. From Table 3, we can find that the correct recognition rate is decreased greatly if there is no feature concerning mouth. Therefore, it is concluded that the features concerning mouth are the most important geometrical features for emotion recognition. On the other hand, we can find that the correct recognition rate is not affected so much if there are no features concerning eyes. Therefore, the geometrical features concerning eyes do not play an important role in emotion recognition. But from the psychological experiments of Sui and Ren found that the eyes play an important role in emotion; therefore, we may draw a conclusion that the geometrical features concerning mouth are the most important in the
geometrical features for emotion recognition, and the geometrical features concerning eyes are not so important. Furthermore, the important features concerning eyes for emotion recognition should be discovered and used in emotion recognition in the further work. Meanwhile, we can find that the correct recognition rate is decreased in CKACFE more than in JAFFE and CQUPTE. Therefore, we can draw a conclusion that the geometrical features concerning mouth are more important for emotion expression for the Caucasian than the eastern people.

Table 3:

<table>
<thead>
<tr>
<th></th>
<th>SARA reserved</th>
<th>ALL features</th>
<th>No mouth</th>
<th>No eyes</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>CRR</td>
<td>RAN</td>
<td>CRR</td>
<td>RAN</td>
</tr>
<tr>
<td>CKACFE</td>
<td>76.01</td>
<td>11.25</td>
<td>79.80</td>
<td>33</td>
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<td>JAFFE</td>
<td>69.37</td>
<td>11.5</td>
<td>74.46</td>
<td>33</td>
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<tr>
<td>CQUPTE</td>
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<td>14</td>
<td>93.86</td>
<td>33</td>
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<tr>
<td>average</td>
<td>79.28</td>
<td>12.25</td>
<td>82.71</td>
<td>33</td>
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CONCLUSION

This project based on rough set theory and the idea of domain oriented data driven data mining, a novel attribute reduction algorithm named SARA is proposed for feature selection for emotion recognition. The proposed method is found to be effective and efficient, and the geometrical features concerning mouth are found to be the most important geometrical features for emotion recognition.
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