Emotion Recognition from the Lip-Contour of a Subject Using Artificial Bee Colony Optimization Algorithm

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Abstract. This paper provides an alternative approach to emotion recognition from the outer lip-contour of the subjects. Subjects exhibit their emotions through their facial expressions, and the lip region is segmented from their facial images. A lip-contour model has been developed to represent the boundary of the lip, and the parameters of the model are adapted using artificial bee colony (ABC) optimization algorithm to match it with the boundary contour of the lip. An SVM classifier is then employed to classify the emotion of the subject from the parameter set of the subjects' lip-contour. The experiment was performed on 50 subjects, and the average case accuracy in emotion classification is found to be 86%.

Keywords: lip contour, artificial bee colony optimization algorithm, support vector machine.

1 Introduction

Emotion recognition is currently gaining importance for its increasing scope of applications in human-computer interactive systems. Several modalities of emotion recognition, including facial expression, voice, gesture and posture have been studied in the literature. Among the well-known methods of determining human emotions, schemes proposed by Ekman and Friesen, Kobayashi and Hara, Cohen et al. deserve special mention. However, we are afraid that there exists hardly any significant work [3] on emotion recognition by a single facial feature. This paper takes a serious attempts to recognize human emotion by considering the lip-contour of the subject.

In this paper we select a 6-segments lip-contour model, whose individual segments can be tuned to all typical non-overlapped lip-contours by controlling model parameters. An Artificial Bee Colony(ABC)optimization algorithm [1]

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is used to match the model lip-contour with the segmented lip boundary of a subject. Experiments with 50 volunteers reveal that there exists a correlation between the lip-contour pattern of the individual, and a specific emotion experienced by the subject. This observation motivates us to design a classifier to map the extracted parameters of the lip-contour model on to the emotional space. We here, select a Support Vector Machine(SVM) classifier for classifying emotion.

The rest of the paper is divided into 5 sections. Section 2 offers the modeling issues of the human lip-contour.We introduce ABC algorithm in section 3. Methodologies are discussed in section 4. Experiments and results are given in section 5. The conclusions are listed in section 6.

2 The Proposed Lip-Contour Model

Until this time, there is no universally accepted model of lip-contour. In this paper, we start with the elementary kiss curve (Fig. 1), and modify it at different segments, as indicated in Fig. 2 to obtain an ideal model of the curve, capable of capturing most of the non-overlapped lip-contours in different emotional states. The basic equation of the kiss curve (Fig. 1) is given by

$$y^2 = (1 - x^2)^3, -1 \leq x \leq 1. \tag{1}$$

The curve returns both positive/negative values of y for each value of x. We, however, use the entire positive half of the curve, and a portion of the negative half. The remaining negative half is replaced by a parabola for better matching with lip profiles of the subjects. When the domain $-1 \leq x \leq +1$ is replaced by $[-l, +l]$, expression (1) is written as

$$y = \left(1 - \left(\frac{x}{l}\right)^2\right)^{\frac{3}{2}} \tag{2}$$

To determine all except the segment GA in Fig. 2, we scaled the right hand side of (2) and added one or more extra terms, as needed, and determine the parameters of the new curve by setting suitable boundary conditions corresponding to the corner points and axis crossings as listed in Table-1 and Table-2. The resulting parameters are also given in the tables.

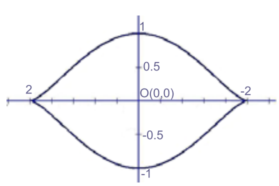

Fig. 1. The standard kiss curve

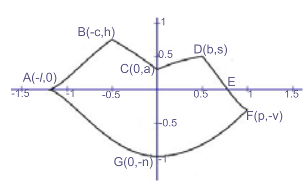

Fig. 2. The proposed model of the lip outer profile

Table 1. The Proposed Lip Segments with boundary conditions

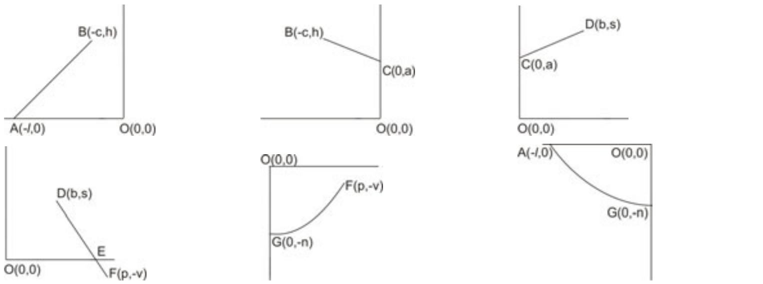

Table 2. Parametric Equations for the Proposed Lip Segments

Curve Segment	Presumed Equation	Boundary Condition	Parameter Obtained by Setting the boundary ions
AB	$y = a_1\left(1-\left(\frac{x}{l}\right)^2\right)^{\frac{3}{2}} + a_2$	$-l \leq x \leq -c$ $0 \leq y \leq h$	$a_1 = \frac{h}{\left(1-\left(\frac{c}{l}\right)^2\right)^{\frac{3}{2}}}$ $a_2 = 0$
BC	$y = a_3\left(1-\left(\frac{x}{l}\right)^2\right)^{\frac{3}{2}} + a_4 x$	$-c \leq x \leq 0$ $h \leq y \leq a$	$a_3 = a$ $a_4 = \frac{a\left(1-\left(\frac{c}{l}\right)^2\right)^{\frac{3}{2}} - h}{c}$
CD	$y = a_5\left(1-\left(\frac{x}{p}\right)^2\right)^{\frac{3}{2}} + a_6 x$	$0 \leq x \leq b$ $a \leq y \leq x$	$a_5 = a$ $a_6 = \frac{s-a\left(1-\left(\frac{b}{p}\right)^2\right)^{\frac{3}{2}}}{b}$
DEF	$y = a_7\left(1-\left(\frac{x}{p}\right)^2\right)^{\frac{3}{2}} + a_8 2$	$b \leq x \leq p$ $s \leq y \leq -v$	$a_7 = \frac{s+v}{\left(1-\left(\frac{b}{p}\right)^2\right)}$ $a_7 = 0$ $a_8 = -v$
FG	$y = a_9 x^2 + a_{10} x + a_{11}$	$p \leq x \leq 0$ $-v \leq y \leq -n$	$a_9 = \frac{n-v}{p^2}$ $a_{10} = 0$ $a_{11} = -n$
GA	$y = \pm\left(1-x^2\right)^{\frac{3}{2}}$	$0 \leq x \leq -l$ $-n \leq y \leq 0$	$y = -n\left(1-\left(\frac{x}{l}\right)^2\right)^{\frac{3}{2}}$

3 The ABC Algorithm

The artificial bee colony optimization (ABC) technique is a population based algorithm for numerical function optimization that draws inspiration from the stochastic behavior of foraging in bees.In ABC trial solution, the population directly affects the mutation operation since it is based on the difference of two members of the population. Hence by this method the information of a good member of the population is distributed among others due to the mutation operation and greedy selection mechanism employed to obtain a new member of the population. In the ABC, while the intensification process is controlled by the stochastic and the greedy selection schemes, the diversification is controlled by the random selection. In ABC algorithm, the colony of artificial bees contains three groups of bees:

– A bee waiting on a dance area for making decision to choose a food source is called an onlooker.
– A bee going to the food source visited by itself previously is named as employed bee.
– A bee carrying out random search is called a scout.

In ABC algorithm, the position of a food source represents a possible solution of the optimization problem and the nectar amount of a food source corresponds to the fitness of the associated solution. The number of employed bees and onlooker bees is equal to the number of solutions in the population. The ABC algorithm consists of following steps:

1. Generate randomly distributed initial population P (g=0) of N_p food sources where, each food source is of dimension D.
2. FOR each i-th employed bee do Generate neighborhood food source

$$X_i^{/} = (x_{i0}, x_{i1}, x_{i2}, ..., x_{i(j-1)}, x_{ij}^{/}, x_{i(j+1)}, ..., x_{i(D-1)}) \tag{3}$$

   with

$$x_{ij}^{/} = x_{ij} + u(x_{kj} - x_{ij}) \tag{4}$$

   where, u is a random variable in [-1,1] and $k \in (0, Np-1), k \neq i$ and $j \in (0, D-1)$
   IF $fit(X_i^{/}) > fit(X_i)$ THEN $X_i = X_i^{/}$
   END FOR.
3. FOR each onlooker bee do Select food source X_i depending on probability

$$p_i = fit(X_i) / \sum_{j=0}^{N_{p-1}} fit(X_j) \tag{5}$$

   Generate $X_i^{/}$ as in equation (3) and (4).
   IF $fit(X_i^{/}) > fit(X_i)$ THEN $X_i = X_i^{/}$
   END FOR.

4. If any food source is abandoned by employed bees, re-initialize the food source by scout bee.
   Repeat steps (1), (2), (3) and (4) until required condition is reached.

4 Methodology

4.1 Segmentation of the Lip-Contour

Several algorithms for the lip segmentation are available in the literature [2], [3]. In this paper, we, however, employ fuzzy k-means clustering algorithm to segment the lip region from the rest of the facial expression. In order to segment the lip region, we first localize the mouth region as shown in Fig. 3.a. Then a conversion from r-g-b to l-a-b color space is undertaken. The k-means clustering algorithm is applied next on this image to get three clusters. The three clusters are: skin, lip and teeth regions. The cluster with the highest intensity variance in l-a-b color space is declared as the lip region. Thus we select the lip cluster (Fig. 3.b) to determine the lip-contour.

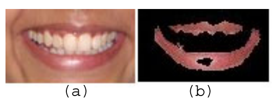

Fig. 3. The segmented mouth region obtained by FCM algorithm

4.2 Parameter Extraction of a Given Lip-Contour Using Artificial Bee Colony Optimization Algorithm

Artificial Bee Colony optimization(ABC) algorithm proposed by Karaboga and Basturk [1] offers promising solution to a global optimization problem. In this paper, we employ artificial bee colony as the optimization algorithm to determine the lip parameters of a given subject carrying a definite emotion.Given a finite set of selected points on the lip boundary of a segmented mouth region, and a model lip curve, we need to match the response of the model curve with the selected data points by varying the parameters of the model curve. The set of parameters for which the best matching takes place between the model generated data points and the selected lip boundary points are the results of a system identification procedure adopted here.

Let, $y = f(x)$ be the model curve. Then for all (x, y) lying on the curve, we obtain $G(x, y) = 1$, and for all points $y \neq f(x), G(x, y) = 0$. Let, $L(x, y) = 1$ for all valid data points on the outer boundary of a segmented lip. We use a performance evaluation metric J, where

$$J = \sum_{\forall x} \sum_{\forall y, y=f(x)} |G(x, y) - L(x, y)| \tag{6}$$

In ABC algorithm, we used J as the fitness functions, where we wanted to minimize J for all valid (x, y) on the lip boundary. The ABC considers 9-parameter food sources, finds out the neighborhood food source by mutation operation, and selects the best of the searched food source and the original food source to determine the parameter vector in the next iteration. This is done in parallel for NP number of parameter vectors, where NP is the population size. The algorithm is terminated when the error limit, defined by the difference of J's between the best of the previous and the current iteration is below a prescribed threshold. The best fit parameter vector is the parameter set of the best model lip-contour matched with a given lip boundary data points.

4.3 Emotion Classification from Measured Parameters of the Lip-Contour Model

It is noted from a large number of lip-contour instances that there exist at least two parameters of the lip model clearly distinctive of individual emotions. So, any typical machine learning/statistical classifier can be employed to classify the different emotional status from the parameter of lip-contour. In this paper, we use Linear Support Vector Machine (SVM) [2] classifier for emotion classification from the lip data.

In our basic scheme, we employed five SVM networks, one each for joy, anger, sadness, fear and relaxation. The i^{th} SVM network is trained with all of the training instances of the i^{th} class with positive levels, and all other training instances with negative levels. The decision logic box driven by the five SVM networks ultimately recognizes the emotion corresponding to the supplied feature vector X.

The decision logic works in the following manner. If only one input of the decision logic is +1, it infers the corresponding class number at the output. For, example, if the SVM-disgust only generates a +1, the output of the decision logic will be the class number for the emotion class: disgust.

When more than one input of the decision logic is +1, the decision is taken in two steps. First, we count the number of positive instances falling in the small neighborhood of the given pattern for each emotion class with its corresponding SVM-output +1. Next, the emotion class with the highest count is declared as the winner. The decision logic thus takes decision based on the principle of "majority voting", which is realized here by the count of positive instances in the neighborhood of the given test pattern. The "neighborhood" here is defined as a 9-dimensional sphere function around a given test pattern, considering it as the center of the sphere. The radius of the sphere is determined from the measurements of standard deviation in the individual features. The largest among the standard deviations for all the features is considered as the radius of the "neighborhood" in the data points, representing positive instances in a given emotion class. The radius of different emotion classes here thus is different. This, however, makes sense as the data density (per unit volume in 9-dimensional hyper space) for different emotion classes is non-uniform.

5 Experiments and Results

The experiment has two phases. In the first phase, we determine weight vectors of 5 SVM classifiers, each one for one emotion class, including anger, disgust, fear, happiness and sadness. We had 50 subjects, and for each subject we obtained 10 facial expressions for 10 different instances of each emotion. Thus for 5 emotions, we had 50 facial expressions for individual subjects. Three out of 10 instances of emotional expression are given in Table 3 for a subject.

Now, for each facial expression given in Table 3, we segmented the mouth region by Fuzzy k-means clustering algorithm, and determined the optimal lip-parameters: b, c, l, p, v, n, a, h and s by adapting the model lip-contour with

Table 3. Facial Expression for Subject 1 for Different Emotions

	Emotion				
Instances	Anger	Disgust	Fear	Happiness	Sadness
1.					
2.					
3.					

Table 4. Lip Parameters for Subject 1 for Different Emotions

Emotion	Instance	b	c	l	p	v	n	a	h	s
HAPPY	1	55	63	226	228	55	194	25	14	0
	2	46	80	221	249	36	241	44	52	44
	3	45	69	221	228	49	156	49	54	49
SAD	1	39	38	170	149	38	64	64	81	75
	2	37	45	171	152	38	45	45	66	53
	3	38	40	164	159	17	67	67	79	74
FEAR	1	48	49	148	142	18	116	46	60	52
	2	45	54	151	167	26	141	38	61	54
	3	44	47	143	151	29	126	36	54	44
DISGUST	1	41	40	190	168	26	96	10	24	19
	2	35	36	187	159	22	92	12	27	23
	3	39	48	176	165	30	98	12	29	18
ANGER	1	36	48	147	143	33	133	31	49	40
	2	32	48	161	168	25	134	26	45	35
	3	33	39	140	144	25	127	42	53	49

the outer boundary of individual segmented lips to have an optimal matching between the two. This matching was performed by ABC algorithm. Table 4 shows the result of lip-parameters obtained from Table 3. The weight vectors for the SVM classifiers for individual emotion of a subject are then identified. This is done by first preparing a table with 10 positive and 40 negative instances for each emotion classes of a subject. The weight vector for the given SVM-classifier for the emotion class is determined in a manner, so that all the positive and negative instances are separated with a margin of $\frac{2}{\|W\|}$. This is done for all individual subjects separately.

The second phase of the experiment starts with an unknown facial expression of a known subject. We first obtain mouth region from the image by Fuzzy K-means clustering, and determine lip-parameter by ABC using the model-lip. Now, we feed the lip-parameters to all the 5 SVM classifiers for the person concerned. The output of one or more SVM-classifiers may be +1. The decision logic then determines the emotion class of the unknown pattern.

6 Conclusion

The chapter proposed a new approach to emotion classification from the lip-contour of the subjects experiencing a specific emotion. Experiments with large number of subjects confirm that the proposed model can capture most of the experimental lip-contour for a specific emotive experience of the subject. The ABC algorithm used here is very fast and robust and thus can easily determine the parameters of the lip-contour. The SVM classifier, which is already an established tool for pattern classification with high accuracy has been utilized here for classifying lip parameters onto emotions. Experiments here too confirm that the percentage accuracy in classification of emotion on an average is 86% as obtained from the data set of 50 Indian subjects each having ten frames per emotion.

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