

# A New Semi-supervised Method for Lip Contour Detection

Kunlun Li, Miao Wang, Ming Liu, Ruining Xin, Pan Wang

College of Electronic and Information Engineering, Hebei University, Baoding, 071002, China

E-mail: likunlun@hbu.edu.cn, hbhdwm800@sina.com

**Abstract**—Lip contour detection is regarded as an essential issue in many applications such as personal identification, facial expressions classification, and man-machine interaction. Moreover, semi-supervised learning is utilized to automatically exploit unlabeled data in addition to labeled data to improve the performance of certain machine learning approaches. In this paper, three contour preprocessing approaches for eliminate lip image noise, i.e., Average filtering, Bilateral filtering, and Edge preserving smoothing techniques are compared. Furthermore, a hybrid approach combing level set theory and semi-supervised Fisher transformation for lip contour detection is proposed. Experiment results show that the proposed semi-supervised strategy for lip contour detection is effective.

**Index Terms**—Semi-supervised learning, level set, lip contour diction, semi-supervised FDA

## I. INTRODUCTION

Lip contour detection is a challenging and an important issue in computer vision due to the variation of human's expressions and environmental conditions. It has got numerous applications in computer vision such as audio-video speech and speaker recognition and so on.

Lip contour detection is an active research topic. The related methods can be classified into three categories. The first category is threshold based method [1, 2], which enjoys a central position in applications of image segmentation because of its intuitive properties. The second is edge and line oriented approaches [3-5], in which lines or boundaries are defined by contrast in luminance, color or texture to be detected. The third is hybrid approaches [6], which aim at consistency between regions and region boundaries.

In our previous relevant research, we have proposed an improved level set method for lip contour detection [xx]. It can optimize the gradient information and enhance the accuracy of the lip contour detection by combining YCbCr color space and Fisher transformation [30]. In literature [31], we improved the Fisher transformation with semi-supervised learning, and combed level set theory with the improved the Fisher transformation.

As is well known, Fisher transformation requires large number of artificial tag data. Therefore, we propose a

hybrid approach combing the improved level set method and semi-supervised Fisher transformation method for lip contour detection in this paper [30, 31]. It comprehensive utilizes the marked and unmarked image pixel information, and obtains good contour extraction results in the cases with fewer tag information.

The rest of the paper is organized as follows. In Section 2, we discuss the preprocessing techniques which aim at improving the results of lip contour detection. We compare the three categories lip contour detection method in Section 3 and propose a new method combines with the semi-supervised learning method in Section 4. Last, we present some experiment results in Section 5 and give the solution in Section 6.

## II. PREPROCESSING

In this section, we describe the Average filtering, Bilateral filtering and Edge preserving smoothing techniques to eliminate noise.

### A. Average Filtering

The average filter aims at smooth image data, thus eliminating noise. This filter performs spatial filtering on each individual pixel in an image in a square or rectangular window surrounding each pixel.

### B. Bilateral Filtering

In Bilateral filtering method[7, 8], the original values of every point in the image are replaced by the average values of the adjacent and gray similar pixel values. The simplest commonly used bilateral filter is moving unchanged Gaussian filter. The Space near degree function and gray scale similar function are the Euclid distance Gaussian function in parameters space.

$$c(\xi, t) = e^{-\frac{1}{2}(\|\xi - x\|/\sigma_d)^2} \quad (1)$$

$$s(\xi, t) = e^{-\frac{1}{2}(\|f(\xi) - f(x)\|/\sigma_r)^2} \quad (2)$$

Where  $c(\xi, t)$  is the space near degree between the point  $\xi$  and the geometric center  $x$ ,  $s(\xi, t)$  is the gray scale similarity between the point  $\xi$  and the geometric center  $x$ .

The average filter and bilateral filtering are very common for removing noise from images. Even the noise reduction can be achieved by these methods, some

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Corresponding author: Kunlun Li, likunlun@hbu.edu.cn

valuable information is lost and the details of object boundaries are deformed. In order to solve such kind of problems, we use the edge preserving smoothing for image preprocessing.

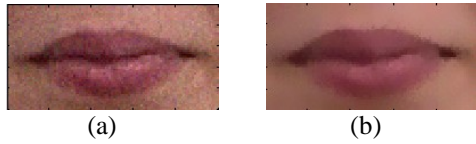


Figure 2. (a) Input image (b) Result of bilateral filtering

C. Edge Preserving Smoothing

The Edge preserving smoothing [9] is an adaptive mean filter where the amount of blurring for each pixel is determined after gathering local information in a specified  $n \times n$  neighborhood. It uses a simple and effective edge preserving smoothing filter, which performs low computation time.

The Edge preserving smoothing filter is applied independently to every image pixel using different coefficients. To calculate the coefficients of the convolution mask for every pixel, Manhattan color distances  $d_i, i=1, \dots, 8$  are extracted between the central pixel and the eight neighboring pixels in a  $3 \times 3$  window, which are normalized in the range [0, 1]. That is:

$$d_i = \frac{|R_{ac} - R_{ai}| + |G_{ac} - G_{ai}| + |B_{ac} - B_{ai}|}{3 \times 255}, 0 \leq d_i \leq 1 \tag{3}$$

Where  $R_{ac}, G_{ac}, B_{ac}$  is the RGB value of the central pixel. To compute the coefficients for the filter's convolution mask, the following equation is used:

$$c_i = (1 - d_i)^p, \text{ where } P \geq 1. \tag{4}$$

As  $p$  gets larger, coefficients with small color distance from the central pixel increase their relative value difference from coefficients with large color distance, so the blurring effect decreases. We select  $p=1,3,5,10$ , for experiments and a fixed value  $p=5$  is used for all of our experiments. The central pixel of the convolution mask is set to zero to remove impulsive noise.

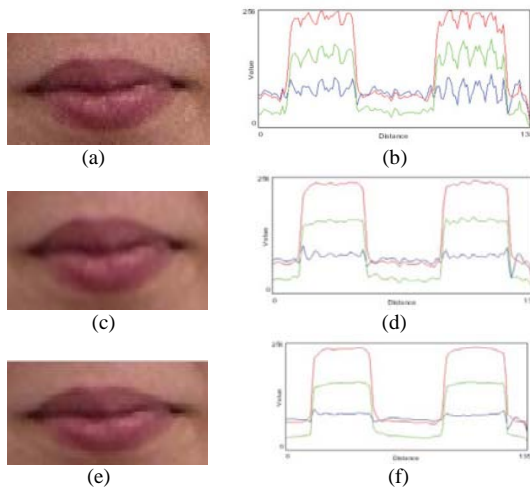


Figure 3 (a) original image (b) the resulted image when the edge preserving smooth method applied fifth ( $p=5$ ) (c) the resulted image when the edge preserving method applied tenth ( $p=10$ ) (d) ~ (f) are the RGB pix value of (a), (b) and (c) respectively.

The preprocessing methods aimed at reducing texture and noise while preserving and enhancing lip contour detection. We compared the average filter, bilateral filtering and edge preserving smoothing and we finally use the edge preserving smoothing method for preprocessing.

III. SOME APPROACHES FOR CONTOUR DETECTION

The contour detection methods can be mainly classified in three categories: threshold based methods, edge and line oriented approaches and hybrid approaches. In this paper we compare the three kinds of methods, and present a hybrid approach combing the improved level set and semi-supervised FDA algorithm for lip contour detection.

A. Threshold based Method

Image threshold segmentation is widely used in image segmentation. The images are considered as the combination of the target area and background region. We select a more reasonable closed value to determine each pixel of the image belongs to target or background region, thus producing corresponding binary image.

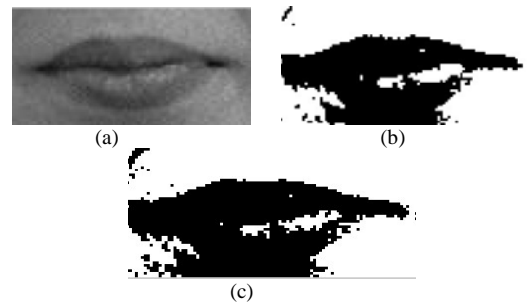


Figure 4 (a) gray image (b) iteration threshold binary image (c) Ostu threshold method

Through the experiments we can see that the results of the threshold method is affected for the difference between grayscale information of lip color and that of skin color is small.

B. Edge and Line Features Oriented Approachs

1. Local contour detector

Differential methods

The earliest linear filtering approaches such as the Sobel, Prewitt, Robert and Canny [10-13] detectors are based on measures of matching between the pixel value on the neighborhood of each pixel, and an edge temple. These methods are belonging to differential methods. The most significant limitation of these methods is that they could not distinguish between texture edges and region boundaries and object contour.

Morphological edge detectors

Mathematical morphology theory is introduced by Matheron for analyzing geometric structure of metallic and geologic samples. It was first used to image analysis by Serra [14]. Based on this theory, mathematical morphology based on set operations, is provided an approach to the development of nonlinear signal

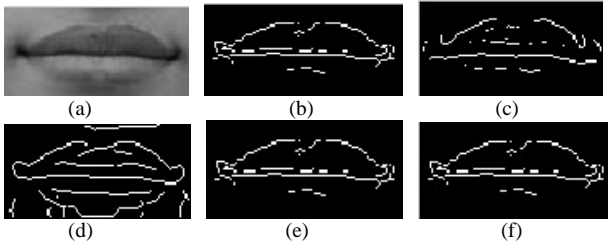


Figure 5 (a)gray image (b)Sobel (c)Log (d)Canny (e)Prewitt (f)Robert

processing operators that incorporate shape information of a signal [15]. In mathematical morphological operations, there are always two sets involved: The shape of a signal is determined by the values that the signal takes on. The shape information of the signal is extracted by using a structuring element to operate on the signal.

There are two basic morphological operators: erosion and dilation. These operators are usually applied in tandem. Opening and closing are two derived operations defined in terms of erosion and dilation. Erosion of a grey-level image  $F$  by another structuring element  $B$ , denoted  $F \ominus B$ , is defined as follows:

$$F \ominus B(m, n) = \min\{F(m+s, n+t) - B(s, t)\}, \text{ where } P \geq 1. \quad (5)$$

Erosion is a “shrinking” operator in the values of  $F \ominus B$ , and it is always less than or equal to the values of  $F$ . Dilation of a grey-level image  $F$  by another structuring element  $B$ , denoted  $F \oplus B$ , is defined as follows:

$$F \oplus B(m, n) = \max\{F(m+s, n+t) + B(s, t)\} \quad (6)$$

Dilation is an “expansion” operator in the values of  $F \oplus B$ , and it is always larger than or equal to the values of  $F$ .

By the erosion and dilation operators defined above, we can detect the edge of image  $F$ , denoted by  $Ee(F)$ , defined as the difference set of the original image  $F$  and the erosion result of  $F$ . This is also known as erosion residue edge detector:

$$Ee(F) = F - (F \ominus B) \quad (7)$$

The edge of image  $F$ , denoted by  $Ed(F)$ , is defined as the difference set of the dilation result of  $F$  and the original image  $F$ . This is also known as dilation residue edge detector:

$$Ed(F) = (F \oplus B) - F \quad (8)$$

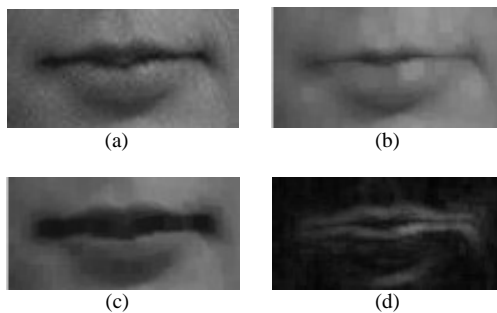


Figure6 (a) gray image (b) dilation (c) erosion (e) morphological edge detection

The traditional morphological algorithms only consider of intensity information of the edge and ignore the direction of the edge. Such methods have some problems due to the edge character information is not comprehensive. The problems are: (1) the detected edges are wider and have lower resolution ratio, (2) if we use the morphological gradient threshold method to detect the edge singly, it will lose part of low intensity edge.

Statistical approaches

In this category of method, we take the EM algorithm and FDA algorithm for example.

(1) Expectation-maximization algorithm

Suppose we have a number of samples drawn from a distribution which can be approximated by a mixture of Gaussian distributions and we wish to estimate the parameters of each Gaussian and assign each datum to a particular one. The Expectation Maximization provides a framework.

Expectation-maximization [16], as expected, works in two alternating steps. Expectation refers to computing the probability that each datum is a member of each class; maximization refers to altering the parameters of each class to maximize those probabilities. Eventually it converges, though not necessarily correctly. The Expectation step is defined by the following equation:

$$E[Z_{ij}] = \frac{p(x = x_i | \mu = \mu_j)}{\sum_{n=1}^k p(x = x_i | \mu = \mu_n)} = \frac{e^{-\frac{1}{2\sigma^2}(x_i - \mu_j)^2}}{\sum_{n=1}^k e^{-\frac{1}{2\sigma^2}(x_i - \mu_n)^2}} \quad (9)$$

This equation states that the expectations or weight for pixel  $z$  with respect to partition  $j$  equals the probability that  $x$  is pixel  $x_i$  given that  $\mu$  is partition  $\mu_i$  divided by the sum over all partitions  $k$  of the same previously described probability. This leads to the lower expression for the weights. The sigma squared seen in the second expression represents the covariance of the pixel data. Once the E step has been performed and every pixel has a weight or expectation for each partition, the M step or maximization step begins. This step is defined by the following equation:

$$\mu_j \leftarrow \frac{1}{m} \sum_{i=1}^m E[Z_{ij}] x_i \quad (10)$$

This equation states that the partition value  $j$  is changed to the weighted average of the pixel values where the weights are the weights from the E step for this particular partition.

Although EM algorithm is an effective method in decision-supporting system, it has the disadvantage of this algorithm is slow convergence. It is not suitable in this experiment for the differences between grayscale information of lip color and that of skin color is small. The experiment results are shown in Figure 7.

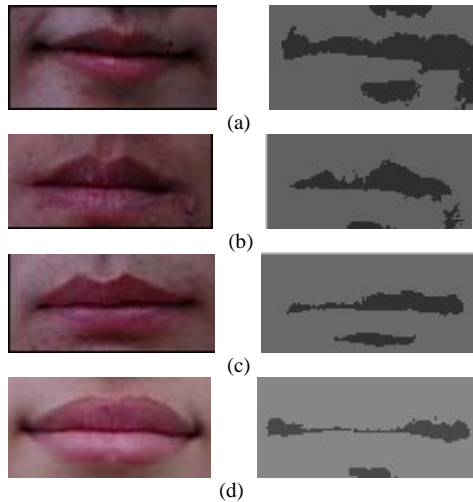


Figure7 the EM algorithm results

## (2) Fisher linear discriminate analysis (LDA)

Fisher linear discriminate analysis (LDA) is a traditional statistical technique. It has been widely used and proven to be successful in many real-world applications. Here we use the Fisher linear discriminate analysis to enhance the gradient information of the lip contour and then we can obtain the lip contour clearly [17].

Here, the G and B components of RGB color space are set to a vector  $x$  which is used to distinguish the lip color and skin color. In the training process, we manually extract patches of 50 people's lips and skin regions as the training samples. By utilizing Fisher transformation to the vector  $x = (G, B)^T$ , we obtain a function that can be used to discriminate the two classes. This function is calculated by using the within-class scatter matrix and defined as:

$$Fisher(x) = W \cdot x^T \quad (11)$$

The projection vector is calculated by:

$$W = S_w^{-1}(m_1 - m_2) \quad (12)$$

The within-class scatter matrix  $S_w$ , is defined:

$$S_w = S_1 + S_2 \quad (13)$$

$$S_1 = \sum (x - m_1)(x - m_1)^T \quad (14)$$

$$S_2 = \sum (x - m_2)(x - m_2)^T \quad (15)$$

The sample mean vector of each class,  $m_k$ , is defined as:

$$m_k = \frac{1}{n_k} \sum_{x \in x_k} x_k \quad (k = 1, 2) \quad (16)$$

Where  $x_k$  is the set of the vectors in  $k^{th}$  class and  $n_k$  is the number of the vectors in the class.

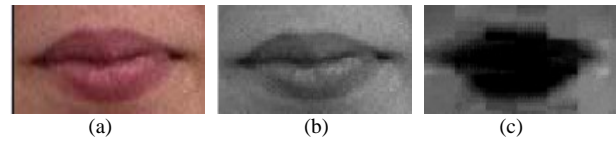


Figure 8 (a) original image (b) gray image (c) the result of FDA algorithm

Figure 8 shows the results before and after Fisher transformation. The approach optimizes the gradient information enhances the accuracy of the lip contour detection by combining of YCbCr color space and Fisher transformation. But this method requires a lot of artificial tag data; which needs a lot of time to mark.

## 2. Global algorithms

Most of the edge features reviewed in this section is based on local method, and a more serious limitation of the aforementioned local method is that the decision of whether a pixel belongs to a contour or not is only based on a small neighborhood of each point. On the other hand, it is easy to produce images in which local patterns are visually similar to an edge do not belong to object contours and vice-versa. So we take into account global information for the contour detection.

Global methods include the level set method and snake model method, the level set is easy to track the topological structure change of the objects, it is a powerful object modeling tool that changing with time.

Level set based method was proposed by Osher and Sethian, it is an effective calculation tool to deal with closed time-evolution movement interface geometric topology change [29].

Given a closed curve  $C$ , the whole plane is divided into the exterior and internal domain of the curve. Define a distance function  $\Phi(x, y, t) = \pm d$  in the plane, and  $d$  represents the shortest distance between the point  $(x, y)$  to the curve  $C$ . The positive and negative sign of the function represent the point in internal domain or external domain of the curve and  $t$  represents time. Curve  $C$  can be represented by the zero level set of the distance function  $\Phi(x, y, t)$ , that is

$$C(t) = \{(x, y) : \Phi(x, y, t) = 0\}.$$

In the evolution process, the curve points always satisfy the following equation:

$$\Phi(x, y, t) = 0 \quad (17)$$

Derivate both sides of the equation (17) of  $t$ , we can get:

$$\frac{\partial \phi}{\partial t} + \frac{\partial \phi}{\partial x} \frac{dx}{dt} + \frac{\partial \phi}{\partial y} \frac{dy}{dt} = 0 \quad (18)$$

Suppose the velocity of all the points on the curve is  $F$ , the level set method limits the movement at various points on the curve is along the curve normal direction, that is, the gradient direction of the points on the curve, therefore the evolution of the entire curve can be expressed as:

$$\frac{\partial \phi}{\partial t} - F |\nabla \phi| = 0 \quad (19)$$

$$\phi(x, y, t) = \phi_0(x, y) \tag{20}$$

Equation (19) is called the level set evolution equation,  $|\nabla \phi|$  indicates gradient norm of the level set function, and  $F$  is the velocity function along the normal direction, which is the direction of the gradient of curve at various points. Equation (20) is the surface equation.

Level set method is an effective tool for describing the curve with curvature related speed evolvement [8]. It has been widely used in image segment and computer visual. It is based on the change of the image gradient. When the object contour is not clear or the gradient information of the image is too weak, the final detection result would be far from the expected. The experiment results is in Figure 9.

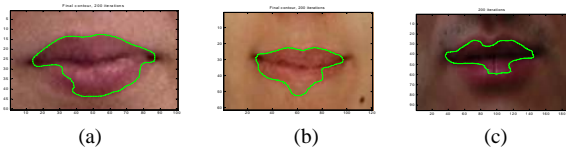


Figure9. The results of the traditional level set method

The level set method described in this Section is based on the change of the image gradient. As Figure 9 shows the contour detection may not be accurate if the object contour is not obvious or the gradient information is too weak.

#### IV. HYBRID APPROACHES

Through the analysis and experiments above, we can see that the three methods have their advantages or shortcomings respectively. The semi-supervised FDA can learn from both labeled and unlabeled data and enhance the gradient information of the lip contour. It can improve the level set method and solve the limitation of the traditional level set method. So in this paper, we present a new hybrid approach combined with semi-supervised FDA method and level set method.

##### A. Semi-supervised Fisher

FDA is a classical supervised learning method. In the context of pattern classification, FDA seeks for the best projection subspace such that the ratio of the between-class scatter to the within-class scatter is maximized. But the labeled data often consume much time and are expensive to obtain, as they require the efforts of human annotators. Contrarily, in many cases, it is far easier to obtain large numbers of unlabeled data. Effectively combining unlabeled data with labeled data is therefore the central task in machine learning.

We introduce some prior knowledge on Semi-supervised learning. We know that unlabeled examples can improve the performance of the learned hypothesis. Semi-supervised learning [18,19] deals with methods for automatically exploiting unlabeled data in addition to labeled data to improve learning performance, where no human intervention is assumed.

In semi-supervised learning, a labeled training data set  $L=\{(x_1,y_1), (x_2, y_2), \dots, (x_{|L|}, y_{|L|})\}$  and an unlabeled

training data set  $U=\{x_1', x_2', \dots, x_{|U|}'\}$  are presented to the learning algorithm to construct a function  $f: X \rightarrow Y$  for predicting the labels of unseen instances, where  $X$  and  $Y$  are respectively the input space and out space,  $x_i, x_j' \in X$  ( $i=1,2, \dots, |L|, j=1,2, \dots, |U|$ ) are  $d$ -dimensional feature vectors drawn from  $X$ , and  $y_i \in Y$  is the label of  $x_i$ . Usually  $|L| \ll |U|$ .

It is regarded that semi-supervised learning originated from [20]. In fact, some straight forward use of unlabeled examples appeared even earlier [18-21]. Due to the difficulties in incorporating unlabeled data directly into conventional supervised learning methods and the lack of a clear understanding of the value of unlabeled data in the learning process, the study of semi-supervised learning attracted attention only after the middle of 1990s. As the demand for automatic exploitation of unlabeled data increases and the value of unlabeled data was disclosed by some early analyses [23, 24], semi-supervised learning has become a hot topic.

In this paper, we improve the traditional FDA [28] by using Semi-supervised learning strategy. The following is the algorithm steps of the algorithm:

a) Find a orthogonal basis of the subspace  $R(X_k)$  : Perform singular value decomposition of  $X_k$  as  $X_k = U \sum V^T$ .  $U = [u_1, \dots, u_r, u_{r+1}, \dots, u_m]$  is the orthogonal matrix, where  $r$  is the rank of  $X_k$ . The vector set  $\{u_1, \dots, u_r\}$  forms a orthogonal basis of  $R(X_k)$ . The matrix  $P = [u_1, \dots, u_r]$  gives a vector space projection from  $R^m$  to subspace  $R(X_k)$ .

b) Map data points into subspace  $R(X_l)$ :

$$x_i \rightarrow z_i = P^T x_i, i = 1, \dots, l, l+1, \dots, n \tag{21}$$

c) Construct the scatter matrixes: Construct the between-class scatter matrix  $S_b$  and total scatter matrix  $S_t$  as

$$S_b = Z_l B Z_l^T = P X_l B X_l^T P^T \tag{22}$$

$$S_t = Z_l C Z_l^T = P X_l C X_l^T P^T \tag{23}$$

d) Eigen-problem: when  $k=n$ , we use regularization to ensure the nonsingularity of  $S_i : S_i = S_i + \delta I_r$ , where  $\delta$  ( $\delta > 0$ ) is the regularization parameter and  $I_r$  is the  $r \times r$  identity matrix. Compute the eigenvectors with respect to the nonzero eigen-values for generalized eigenvector problem:

$$S_b b_i = \lambda_i S_i b_i, i = 1, 2, \dots, c-1 \tag{24}$$

We obtain the transformation matrix  $B = [b_1, \dots, b_{c-1}]$ .

e) Construct the adjacency graph: Construct the  $p$ -nearest neighbor graph matrix  $W$  as in (23) to model the relationship between nearby data points and calculate the graph Laplacian matrix  $L = D - W$ .



f) Eigen-problem: Compute the eigenvectors with respect to the nonzero eigenvalues for the generalized eigenvector problem:

$$S_b a_i = \lambda(aS_i + (1 - \alpha)PXLX^T P^T) a_i, i = 1, \dots, c - 1 \quad (25)$$

There are at most  $c-1$  nonzero eigenvalues for the eigenvector problem. We obtain the transformation matrix  $A=(a_1, \dots, a_{c-1})$ .

g) Embedding: The data point can be embedded into  $c-1$  dimensional subspace by:

$$x \rightarrow y = A^T z = A^T P^T x = (PA)^T x \quad (26)$$

**B. Hybrid Approaches**

For the Fisher transform requires a lot of time to labor the artificial tag data, we propose the semi-supervised FDA learning based on an improved level set method. It effectively solves the problems. The use of a large number of unlabeled data improves the lip contour extraction efficiency.

The following is the step of this new method:

(1) Apply the Edge preserving smoothing method to reduce texture and noise while preserving and enhancing lip contour detection.

(2) Utilizes the semi-supervised FDA method to enhance the gradient information of the lip contour which using label data and unlabeled data. We take the manual labeling lip color points and skin color points as the labeled data, table 1 is the data sample. The pairwise constraints between the data are generated by the manual tagging data according to their corresponding class labels, the untagged data are generated directly from the remaining unlabeled samples without restriction. After sample training, we use the semi-supervised clustering method to distinguish lip color and color. Figure 11 shows the image clustering results.

(3) Use Gauss filter and morphology corrosion expansion method to remove noise and discrete points.

(4) Apply the level set method on the results of the semi-supervised FDA algorithm and get the segmentation result.

TABLE I.  
SOME MANUAL TAGGED DATA

Lip color pixel point			Skin color pixel point		
G	B	label	G	B	label
34	33	0	79	87	1
33	37	0	72	78	1
90	109	0	91	97	1



Figure 10. (a) Original image (b) the result of 20 constrain numbers (c) the result of 50 constrain numbers 50 (d) remove noise and discrete points.(e) segmentation result

**V. EXPERIMENT**

For testing the performances of our approach, we built a color lip image database. The database contains the data of 100 images. The data set included the lighting, facial expressions and attitude changes.

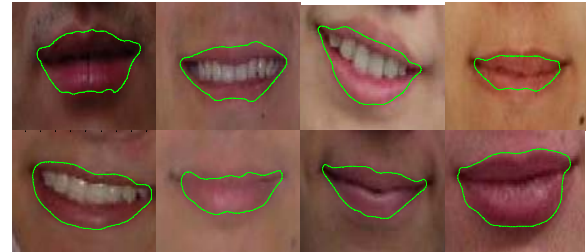


Figure 11. Some of the accuracy results of the lip contour detection



Figure 12 depicts such poor detection results.

Figure 11 shows some of the better results. From failure cases of our method we observed that there are leakages between upper lip, nose and around the edge of the lip. Figure 12 depicts such poor detection results.

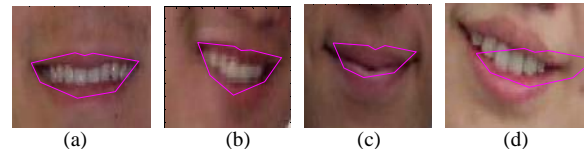


Figure 13. Detection results of the traditional ASM method

We compared the improved approach with the traditional Active Shape Models. Figure 13 shows the detection results by using traditional ASM. The traditional ASM needs a large set of training set to include all types of lips, the accuracy and speed depend on the initialization of the model parameters. It will increase the contour matching scope and impact detection speed if the initialization is not accurate. It is also often trapped in local optimizing problem, while the improved level set method avoids the problem of easily falling into local optimizing.

**VI. CONCLUSION**

In this paper, we contrast three contour preprocessing methods for eliminating lip image noise, i.e., average filtering, bilateral filtering, and edge preserving smoothing technique. Moreover, the two approaches for lip contour detection, i.e. the threshold based method and the edge and line oriented approaches are also compared. Table 1 lists the comparison of the three category contour detection approaches. Basing on the experiment results and analysis of the advantage and disadvantage of these

TABLE II.

THE COMPARISON OF THE THREE CATEGORY CONTOUR DETECTION APPROACHES

Contour detection method	Example	Advantages	Dis-advantages
Threshold based method	Ostu threshold method	Simple and easy to implement	more sensitive to the noise of the input images
Edge and line oriented approach	Differential methods	Fast and conceptually simple	Fail in capturing mid-level and high-level visual cues.
	Statistical approaches	EM: a good way in decision-supporting system	EM: slow convergence
		FDA: conceptually simple	FDA: the labeled data often consume much time and are expensive to obtain
	Semi-supervised FDA: automatically exploiting unlabeled data in addition to labeled data to improve learning performance		
Global algorithm	Higher performance	Computationally more demanding	
Hybrid approaches	Level set method+ Semi-supervised FDA	Good performance	

approaches, we propose a hybrid approach combines with level set method and semi-supervised Fisher transformation method for lip contour detection. We apply the semi-supervised idea for the lip contour detection and improve the accuracy of detecting the lip contours. The proposed method can efficiently reduce the time complexity and human annotators' efforts. The experimental results demonstrate that the proposed method can improve the accuracy of detecting the lip contours.

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**Kunlun Li** born in 1962, received his Ph.D in school of computer and information technology from Beijing Jiaotong University. Currently he is a professor in College of Electronic and Information Engineering, Hebei University. His main research interests include pattern recognition and artificial intelligent, machine learning and data mining, information security, biological information

and image processing.



**Miao Wang** was born in 1986, received her B.E. degree in College of Electronic and Information Engineering, Hebei University. Currently she is a M.E. candidate in College of Electronics and information Engineering, Hebei University. Her main research interests include pattern recognition and image processing.

**Liu Ming** received the B.S. and the M.S. degree in applied mathematics and computer science from Hebei University, Baoding, China, in 1991 and 2000, and the Ph.D. degree in signal and information processing from Beijing Jiaotong University in 2009. He is currently a Associate Professor in the College of Electronic and information Engineering, Hebei University. His main research interests include biometrics and computer vision.

**Ruining Xin** was born in 1986, received her B.E. degree in Hebei University. Currently she is a M.E. candidate in College of Electronics and information Engineering, Hebei University. Her main research interests include pattern recognition and image processing.

**Pan Wang** was born in 1988, received her B.E. degree in Hebei University. Currently she is a M.E. candidate in College of Electronics and information Engineering, Hebei University. Her main research interests include pattern recognition and image processing.