Lip Processing and Modeling based on Spatial Fuzzy Clustering in Color Images

R. Rohani, F. Sobhanmanesh, S. Alizadeh, and R. Boostani

Abstract

In this paper, a robust pre-processing algorithm based on spatial fuzzy clustering for a model based lip contour extraction is presented. This transformation aims at increasing discrimination between lips and skin to enhance the lip contour detection. For each pixel in the transformed data, a and b components of CIELAB color space are used as features in spatial fuzzy clustering phase. The employed clustering method takes into account both the distributions of data in feature space and the spatial interactions between neighboring pixels during clustering. Then, an elliptical and a Gaussian mask delete the pixels around lip that were previously clustered as lip pixels. Finally, a model is fitted upon the lip for extracting the lip contour. To show the effectiveness of the proposed method, pseudo hue segmentation and spatial fuzzy c-mean clustering were implemented and compared to our method. The results on VidTIMIT and M2VTS databases show that the novel scheme is able to extract the lip contour even in the situations that the nose and neck appeared in the lip region. Empirical results showed our method outperformed the present state-of-art methods.

Keywords: Lip-reading, Spatial Fuzzy clustering, Pseudo hue, Lip model.

1. Introduction

One of the major weaknesses of current automatic speech recognition (ASR) systems is their sensitivity to environmental and channel noises [15, 16]. Many applications deal with this problem such as special audio preprocessing techniques and noise adaptation algorithms [4]. To overcome this problem, one approach is to take both video and speech of a speaker simultaneously and process them together in order to get higher speech recognition. The mentioned scheme is the base of audio-visual speech recognition systems which make a decision based on processing of both modalities. For example in the case of human listener, visual information such as facial expressions, lips and tongue movements are used to improve speech understanding compare to using only speech signal. The visual part is independent of all acoustic noises therefore; result of this modality can be employed as auxiliary information to enhance the speech recognition rate. Nevertheless, extracting informative features from lip motion of a speaker needs to apply a proper detection method to extract lip contour in successive image frames. Active shape methods [6] as one of the lip contour detection methods have been used in several researches [17, 18], but these methods often converge to inaccurate results when the lip edges are unclear or color of lip and skin is fairly close together. Moreover, these methods have some parameters that need a large training set to estimate them significantly and consequently to detect lip shapes accurately. To make lip contour detection more robust, Liew et al. [10] proposed a deformable model-based approach to extract lip contour by using lip color compare to skin color. Their method partitioned a given color lip image into lip and non-lip regions based on intensity and color using spatial fuzzy C-mean clustering and then represent the detected lip with a geometric lip model. In contrast, when lip region contains other parts of the face like nose or neck, inputs are not discriminative enough for clustering and the methods mostly failed to detect a precise lip contour. In this study, our contribution is to apply a preprocessing based on RGB color space proposed by [1] and use the transformed data with b component of CIELAB color space [7] to cluster each pixel even in regions include some parts of neck or nose. The processed images are used in clustering to partition regions into two clusters including lip and non-lip. In the clustering phase, we use spatial fuzzy clustering method [13] which used in many image segmentation applications like segmentation of breast lesions in ultrasound images [14] or detection of brain activation regions. The spatial fuzzy clustering algorithm uses the spatial contextual information in an image. The objective function utilizes a new dissimilarity index that takes into account the influence of their neighboring pixels on the center of a 3x3 window. It is an unsupervised learning method where
neither prior assumption of the underlying feature distribution nor the training phase is needed. At the end, a simple and effective geometric lip model that captures the priori lip shape is used.

Our study is totally divided into four stages as shown in Fig. 1. In our scheme, first face is detected and according to prior knowledge that lip is located in the lower part of face, the one third lowest part of each full-face image is localized as a region which contains the lip. Then this region is transformed by pseudo-hue and then clustered by fuzzy spatial technique into lip and non-lip areas and finally the lip contour is geometrically modeled and extracted. The rest of this paper is structured as follows. The proposed algorithm is presented in Section 2, which includes image preprocessing, spatial fuzzy clustering method and lip modeling. Section 3, presents and discusses the experimental results obtained from the proposed algorithm and compare it with other state of the art methods on M2VTS and VidTIMIT databases. Finally, the paper is concluded in section 4.

2. Lip contour extraction

To detect the lip contour in the lower part of face, full-face should be first detected in each frame. In order to do this, we used local SMQT features and split up Snow classifier [5]. Then, lip location is determined in the lower part of the full-face image. In order to extract the visual speech features, accurate lip shape detection is essential. The use of edge-based approach for lip extraction is problematic since the resulted edge maps are usually very noisy along with many false edges. Moreover, edges are often absent on the lip boundary or in some cases they have very low magnitude and can often be overwhelmed by strong false edges not associated with the lip boundary. For these reasons, our lip extraction approach does not rely on detecting edges on the lip boundary. Instead, our approach is aimed at finding an optimum partitioning of a given lip image into lip and non-lip regions based on the pixels in terms of their intensity and color. The partitioning does not presume the lip to be of any particular color, but it focuses on color and intensity differences between the lip and non-lip areas. Besides the additional information it provides, color is also a more stable object reflectance property and is less affected by illumination. In the following sections, we will elaborate on the employed lip model, the cost function for finding the optimum partitioning and the optimization algorithm applied to the model parameters.

A. Image preprocessing

Liew et al. [10] used the CIELAB, CIELUV color spaces for preprocessing of lip images. A feature vector containing \( \{L, a, b, u, v\} \) is constructed for each pixel in an image, where \( L' \) is a normalized luminance parameter. These features are used for the clustering
phase which detects the lip contour efficiently when the lip region consists of just lip, but in practice we could not obtain such a localized image. Fig. 3(b) shows the weakness of these features for clustering when parts of the nose and lip are appeared in the localized image. To solve this problem, before clustering, we introduced a new preprocessing algorithm and applied it to each localized image that is described in the following section.

I. Color mixture analysis of skin and lips
A robust preprocessing algorithm for lip segmentation has been presented by Eveno et al. [1]. They used color space in which lips and skin have more discriminative features. Skin area is better characterized by chromatic components rather brightness components. Even for different people, chromatic skin features are relatively constant while illumination variation is significant. To detect it, RGB images are transformed such that brightness components is discarded and only chromatic information is kept and employed for the segmentation. In RGB space, the difference between red and green is higher for lips rather skin, which can be seen in Fig. 2. Pseudo hue definition that exhibits this difference is computed as follow:

\[
h(x, y) = \frac{R(x, y)}{G(x, y) + R(x, y)}
\]

where \(R(x, y)\) and \(G(x, y)\) are respectively the red and the green components of the pixel \((x, y)\). As it is shown in Fig. 3(b), this parameter reveals a significant difference between the lip and skin regions.

II. CIELAB color space
CIELAB color space [7] is the second system adopted by CIE as models which enhanced uniform color spacing in their values. CIELAB is an opponent color system based on the earlier system of Richard Hunter called L, a, b [7]. Color opposition correlates with discoveries in the mid-1960s that somewhere between the optical nerve and the brain, retinal color stimuli are translated into distinctions between light versus dark, red versus green, and blue versus yellow. CIELAB indicates these values with three axes: \(L^*, a^*, b^*\) can be seen in Fig. 4.

The central vertical axis represents lightness (signified as \(L^*\)). The color axes are based on the fact that a color cannot be both red and green, or both blue and yellow, because these colors oppose each other. On each axis the values run from positive to negative. On the \(a-a'\) axis, positive values indicate amounts of red while negative values illustrate amounts of green. On the \(b-b'\) axis, yellow is positive and blue is negative.

B. Spatial Fuzzy Clustering
Clustering is an unsupervised exploratory data analysis method applied to data in order to discover structures or certain groupings, clusters, in a dataset based on similarity or distance criterion. It is the process of dividing data elements into groups or clusters such that items in the same cluster are as similar as possible, and items in different clusters are as dissimilar as possible. Fuzzy C-means (FCM) is a method of clustering which allows data points belong to more than one cluster with different degrees of belonging or membership to different clusters, measured as degrees in \([0,1]\). FCM is based on an objective function, similar to a cost function, which should be minimized to give the optimal cluster solution. This method (developed by Dunn [8] and improved by Bezdek [9]) is frequently used in many applications [10, 11]. This can result in a much finer details of the data model. For data with an inherent spatial ordering such as image data, the spatial information can affect the clustering results. Furthermore, many pixels in real images are very ambiguous...
especially in the overlapping regions of two clusters. But if the contextual information is utilized, the ambiguity will be reduced. Liew et al. [13] applied a modified fuzzy clustering called spatial fuzzy clustering, SFCM, to the image and used it for lip segmentation in [10, 12]. This algorithm utilizes the spatial information and the objective function includes a new dissimilarity index that takes into account the influence of neighboring pixels upon the center pixel of 3 × 3 window. The new index is adaptive to the image content within the window. If a window is in a non-homogeneous region, the effect of neighboring pixels on the center pixel is reduced; otherwise the center pixel is smoothed by its neighboring pixels during the computation of membership values and cluster centroids. The proposed algorithm is more tolerant to noise and better at resolving classification ambiguity. Highly overlapped clusters will be merged. This merging scheme results in an optimal partitioning of data automatically. SFCM can deal better with different cluster shape and size than the conventional FCM.

Let \( X = \{ x_{i,1}, ..., x_{i,j}, ..., x_{n_1,n_2} \} \) be the set of feature vectors with an image \( I \) of size \( n_1 \times n_2 \) where \( x_{i,j} \in R^p \) is the \( p \)-dimensional feature vector at location \( (i,j) \).

Let us define a weighting function as

\[
\lambda(\theta) = \frac{1}{1 + e^{-(\theta - \mu)/\sigma}}
\]

The parameter \( \mu \) specifies the displacement of \( \lambda \) from \( \theta = 0 \) and \( \sigma \) determines the steepness of the sigmoid curve. For each pixel, the Euclidean distance between its feature vector and the feature vector of its neighbors can be computed. \( \partial_{(r,s),(r-1,s-1)} \) denotes as the Euclidean distance between feature vector \( x_{r,s} \) and its neighbor \( x_{r-1,s-1} \):

\[
\partial_{(r,s),(r-1,s-1)} = (x_{r,s} - x_{r-1,s-1}) \cdot (x_{r,s} - x_{r-1,s-1})
\]

Let \( d_{i,r,s} \) be the Euclidean distance between the feature vector \( x_{r,s} \) and the cluster centroid \( v_i \). Taking the 8-neighborhood of \( (r,s) \) into account and letting \( \lambda(\partial_{(r,s),(r+s+1)}) = \lambda_{i,(r,s)} \), a dissimilarity index \( D_{i,r,s} \) which measure the dissimilarity between \( x_{r,s} \) and \( v_i \) is defined as,

\[
D_{i,r,s} = \frac{1}{8} \sum_{l_1 = -1}^{1} \sum_{l_2 = -1}^{1} d_{i,r,s}^2 \lambda_{i,l_1,l_2}^2 + d_{i+1,r+s,l_1,l_2}^2 (1 - \lambda_{i,l_1,l_2} \lambda_{i,l_1,l_2})
\]

with \( (l_1,l_2) \neq (0,0) \).

The objective function of SFCM is given by

\[
J_m(u,v) = \sum_{r=1}^{n_1} \sum_{s=1}^{n_2} \sum_{i=1}^{c} u_{i,r,s}^m D_{i,r,s}
\]

Subject to

\[
\sum_{i=1}^{c} u_{i,r,s} = 1 \ \forall (r,s) \in I
\]

where the \( c \times n_1 n_2 \) matrix \( U \in M_{fc} \) is a fuzzy \( c \)-partition of \( X \), \( v = \{ v_1, v_2, ..., v_c \} \in R^P \) is the set of fuzzy cluster centroids, \( m \in (1, \infty) \) defines the fuzziness of clustering, \( c \) is the number of clusters and the value \( u_{i,r,s} \) gives the membership of pixel \( (r,s) \) in fuzzy cluster of \( C_i \). Solving of the following equation (7) leads to achieve stationary points of \( J_m \):

\[
\min_{(u,v)} (J_m(u,v))
\]

Results of applying spatial fuzzy clustering algorithm to different images are illustrated in Fig. 5. In 5(a), clustering algorithm was applied to an image including just the lip region. When this algorithm is imposed to the image including lip and some part of nose and neck, it has failed just as shown in Fig. 5(b). Thus, applying the mentioned preprocessing methods provide more discriminant features consist of \( \{ h, b \} \) which used as spatial fuzzy clustering input to obtain better results which can be seen in Fig. 5(c). To enhance separation of lip from non-lip pixels, a post processing stage is proposed which explained in the next part.

C. Image post processing

To locate the mouth region and remove any erroneous blobs that are left behind, after morphological filtering, Leiw et al. [10] utilized the best-fit ellipse and weighed down high probable pixels outside of the fitted ellipse. Parameters of the best-fit ellipse, i.e., the center of mass \( (x_m, y_m) \), the inclination \( \theta \) around the center of mass, the semi-major and semi-minor axes, \( x_a \) and \( y_a \) are computed by the following formulas:

\[
x_m = \sum_{x=1}^{M} \sum_{y=1}^{N} x \ast \text{prob}(x,y) / \sum_{x=1}^{M} \sum_{y=1}^{N} \text{prob}(x,y)
\]

\[
y_m = \sum_{x=1}^{M} \sum_{y=1}^{N} y \ast \text{prob}(x,y) / \sum_{x=1}^{M} \sum_{y=1}^{N} \text{prob}(x,y)
\]

\[
\theta = \frac{1}{2} \tan^{-1} \left( \frac{2 \mu_{11}}{\mu_{20} - \mu_{02}} \right)
\]

\[
x_a = \left( \frac{x}{\pi} \right)^{1/4} \left( \frac{I_y}{I_x} \right)^{3/8} \text{prob}(x,y)
\]

\[
y_a = \left( \frac{y}{\pi} \right)^{1/6} \left( \frac{I_x}{I_y} \right)^{3/8} \text{prob}(x,y)
\]

where \( M, N \) are the dimensions of the column and row, respectively. The \( (p,q) \)-th order central moment \( \mu_{pq} \), the column and row moments of inertia, \( I_x \) and \( I_y \), are given by:

\[
\mu_{pq} = \sum_{x=1}^{M} \sum_{y=1}^{N} (x - x_m)^p (y - y_m)^q \text{prob}(x,y)
\]
As shown in equation (11), $x_o$ and $y_o$ are evaluated using the moment of inertia of an ellipse with unity density of mass. The inclination angle $\theta$ is obtained by minimizing $I_x$ in (13) with respect to $\theta$ such that the semi-major and semi-minor axes are maximized and minimized respectively. Fig. 6(b) shows an image after applying the best-fit ellipse to the clustered image. For detecting two lip corners a $1 \times 5$ mask $\left[\frac{1}{5}, \frac{1}{5}, \frac{1}{5}, \frac{1}{5}, \frac{1}{5}\right]$ is convolved with the clustered image. This mask highlights the points which have high correlation with their horizontal neighbors. Then, two left and right farthest points with the probabilities higher than a threshold are chosen as lip corners. After applying the ellipse to the clustered image and detecting lip corners, we proposed another post processing task by multiplying a Gaussian mask by pixels inside the ellipse. Center of this mask is placed on the middle point of lip (between left and right corners). The final segmented lip image can be seen in Fig. 6(c).

**D. Lip modeling**

Liew et al. [10] proposed a geometric deformable model for the lip shape. The model enables a priori knowledge about the expected lip shape to be incorporated. A geometric model allows the lip shape to be described by a small set of parameters with clear physical interpretation of each parameter. The geometric lip model as shown in Fig. 7 is described by the following equations:

\[
y_1 = h_1 \left( \frac{x - y_2}{w} \right)^{1 + \delta^2} - h_1
\]

\[
y_2 = \frac{-h_2}{(w - x_{off})^2} \left( |x - y_2| - x_{off} \right)^2 + h_2
\]

For $x \in [-w, w]$ with the origin at $(0,0)$. The physical interpretations of $w, h_1, h_2, x_{off}$ are depicted in Fig. 7. The parameter $s$ describes skewness of the lip shape and the exponent $\delta$ describes the deviation of the curve from a quadratic one. The exponent $\delta$ is raised by power of two in order to ensure that $1 + \delta^2$ is always equal or bigger than 1 where $\delta$ is a real number. The exponent $\delta$ allows the lip model to be fitted upon lips with different degrees of curvature. When the origin of the model is located at $(x_c, y_c)$ and the lip is inclined at angle $\theta$ with respect to $(x_c, y_c)$, equations (9) and (10) are modified by replacing $x$ and $y$ by $(x - x_c)\cos \theta + (y - y_c)\sin \theta$ and $-(x - x_c)\sin \theta + (y - y_c)\cos \theta$, respectively. The set of parameters that control the lip shape are then given by
\[ p = \{x_c, y_c, w, h_1, h_2, x_{off}, \delta, s, \theta\} \]

I. **Cost function formulation**

In this part the goal is to segment a lip image into a foreground and a background region, which are corresponded to the lip and non-lip regions, respectively. If \( \text{prob}(x,y) \) is considered to be the probability of being a lip pixel for each image pixel \((x,y)\), then the following cost function which leads to a maximum likelihood criterion can be used to determine an optimum foreground–background partitioning, i.e., the optimum region boundary \(B^*\).

\[
C(B) = \prod_{i=1}^{2} \prod_{(m,n) \in R_i(B)} \text{prob}(m,n), \tag{17}
\]

where \(R_1(B)\) and \(R_2(B)\) are the foreground lip region and background non-lip region, respectively, \(\text{prob}(m,n)\) is the probability of pixel at location \((m,n)\) being a lip pixel, and \(\text{prob}_2(m,n) = 1 - \text{prob}_1(m,n)\) is the probability of pixel at location \((m,n)\) being a non-lip pixel. Maximization of \(C(B)\) will give an optimum boundary \(B^*\) such that \(R_1(B^*)\) and \(R_2(B^*)\) contains pixels which maximize functions of \(\text{prob}_1\) and \(\text{prob}_2\), respectively. By taking logarithm, maximization of (17) would be equivalent to minimization of the following relation.

\[
E(B) = - \sum_{(m,n) \in R_1(B)} \text{prob}_1(m,n) - \sum_{(m,n) \in R_2(B)} \text{prob}_2(m,n), \tag{18}
\]

However, in equations (17) and (18), \(m\) and \(n\) are discrete values. Thus, the boundary \(B\) is discrete in the sense that it is only defined on the discrete pixels points on the boundary of region \(R_1\). This is clearly inadequate for our purpose since our lip model consists of continuous curves and an arbitrary point on the curve does not always fall on integer grid position. To overcome the above shortcoming, we generalize Eq. (18) to the continuous setting. At first, we extend discrete values \(m\) and \(n\) to continuous values of \(x\) and \(y\). The boundary \(B\) now becomes continuous and can assume any arbitrary shape. Next, we let

\[
f(m,n) = \int_{m-0.5}^{m+0.5} \int_{n-0.5}^{n+0.5} g(x,y) dy dx \tag{20}
\]

i.e., \(f(m,n)\) is given by the unit area (centered at \((m,n)\)) integration of \(g(x,y)\). Then (18) is generalized to

\[
E(B) = \int_{R_1(B)} g(x,y) dy dx, \tag{21}
\]

where the boundary \(B\) is continuous. Let the boundary \(B\) be specified by our lip model, then the optimum model parameter set \(p^*\) is the one that minimizes the following cost function:

\[
E(p) = - \int_{x_1(p)}^{x_2(p)} \int_{y_1(p)}^{y_2(p)} g(x,y) dy dx, \tag{22}
\]

where \(x_1(p) = x_c - w \cos \theta\) and \(x_2(p) = x_c + w \sin \theta\), are the left and right lip corner points, \(p\) is the set of model parameters, \(y_1(p;x)\) and \(y_2(p;x)\) are the two vertical boundary points of the line \(x\). Given the probability map \(\text{prob}(m,n)\), \(f(m,n)\) can be found by equation (19). Then the continuous cost surface \(g(x,y)\) in equation (22) needs to be generated. If we impose that, the surface \(g(x,y)\) will be piecewise continuous, then a bilinearly interpolated surface which satisfies equation (20) at all grid point \((m,n)\) can achieve the extending task. Given four corner points \(z_{jk}, z_{j+k}, z_{j+k+1}, z_{jk+1}\), the bilinearly interpolated surface is given by

\[
g_{jk}(x,y) = (1 + j - x)(1 + k - y)z_{jk} + (x - j)(1 + k - y)z_{j+k} + (x - j)(y - k)z_{j+k+1} + (1 + j - x)(y - k)z_{jk+1} \tag{23}
\]

where \(x \in [j, j + 1], y \in [k, k + 1]\). Thus the task of generating \(g(x,y)\) becomes that of determining the values of \(\{z_{m,n}\}\). Using (20) and (23) and after some algebraic manipulation, it can be shown that \(z_{m,n}\) and \(f(m,n)\) are related by the following discrete convolution equation:

\[
f(m,n) = \sum_{m=-1}^{1} \sum_{n=-1}^{1} h(m - m, n - n) z_{m,n} \tag{24}
\]

where the convolution mask \(h(m,n)\) is given by the matrix

\[
H = \frac{1}{64} \begin{bmatrix} 1 & 6 & 1 \\ 6 & 36 & 6 \\ 1 & 6 & 1 \end{bmatrix}. \tag{25}
\]

In the frequency domain, (24) becomes

\[
F(\omega_1, \omega_2) = H(\omega_1, \omega_2)Z(\omega_1, \omega_2). \tag{26}
\]

Hence, \(\{z_{m,n}\}\) can be obtained by taking the inverse FFT of the following formula:

\[
Z(\omega_1, \omega_2) = F(\omega_1, \omega_2) / H(\omega_1, \omega_2). \tag{27}
\]

Figure 8. The final resulted image after model fitting.

The boundary pixels in our implementation are handled by symmetric extension. In this work, the parameters \(x_c, y_c, w\) and \(\theta\) are estimated using lip corners. Fig. 8 shows the final result of the proposed model on the lip image.
3. Result

In this work, two audio-visual databases are used to evaluate the proposed algorithm. The M2VTS database [2] contains 185 recordings of 37 subjects (12 females and 25 males), and the other database, VidTIMIT [3], is comprised of video and corresponding audio recordings of 43 volunteers (19 female and 24 male). The results of the contour detection part of our algorithm for different speakers from M2VTS and VidTIMIT databases are shown in Fig. 9. In the first column, Fig. 9(a), the lip regions of original images are illustrated. When spatial fuzzy clustering was applied to these regions using features that used in $\{L, a, b, u, v\}$, the images were clustered into lip and non-lip clusters which shown in Fig 9(b). But the problem is that when the lip image consists of other parts of face, like nose or beard, these
features are not such discriminative as needed. In this work, after preprocessing steps and choosing \( \{h, b\} \) for each pixel as spatial fuzzy clustering input feature vector, more distinguishable results are obtained (see Fig. 9(c)). And finally, the lip model shown in Fig. 9(d) is constructed using the clustered images of Fig 9(c). It can be seen from these results that our method works well even for those images including beard or nose which behave like noise in our processing task.

4. Conclusion

In this paper, a new lip contour extraction method was presented. The new method uses the pseudo hue preprocessing technique on the original images that aims at producing discriminative features between lip and skin regions. Following this step, a feature vector consists of \( \{h, b\} \) is chosen and employed for segmentation step which uses spatial fuzzy clustering method. This clustering method takes both the color information and the spatial distance into account. A function is embedded in the dissimilarity measure of the objective function to differentiate the pixels having similar color information while located in different regions. In other words, it behaves like a noise reduction algorithm. Based on the minimization of the objective function, the algorithm assigns a proper lip being probability value for each pixel in the image. The use of pseudo hue components in spatial fuzzy clustering algorithm allows a more reliable segmentation of the lip region in the face color images than other methods. Moreover, the proposed method is robust even in cases that mouth region image contains other parts of face. This method was compared to pseudo hue segmentation and spatial fuzzy clustering with other features as input. The achieved results by the proposed method outperformed the compared method.

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