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Lips Feature Extractionfor Biometricsusing SOM Paper ID

V.Elavarsi[1]and,V.Subbulakshmi[2]

[1,2]Department of Information Technology, SCAD College of Engineering and Technology

Vannarpet, Tirunelveli 627011

Abstract- The objective of this project is to extract the feature of lips which used in biometric systems. And here the impact of lip identity recognition is investigated. It is a challenging issue for identity recognition solely by the lips. A fast box filtering is proposed to generate a noise-free source with high processing efficiency. Afterward, five various mouth corners are detected through the proposed system, in which it is also able to resist shadow, beard, and rotation problems. And the SVM support vector machine is used to find the directional gradient of the feature points. For the feature extraction, two geometric ratios and ten parabolic-related parameters are adopted for further recognition through the support vector machine. Experimental results demonstrate that, when the number of subjects is fewer or equal to 29, the correct accept rate (CAR) is greater than 98%, and the false accept rate (FAR) is smaller than 0.066%.

The processing speed of the overall system achieves 34.4 frames per second, which meets the real-time requirement. The proposed system can be an effective candidate for facial biometrics applications when other facial organs are covered or when it is applied for an access control system. The proposed system SOM algorithm is used to find the gradients of the feature points. Then the experimental results demonstrate that, the correct accept rate (CAR) is greater and the false error rate is lower than the existing system. Because the SOM algorithm doesn't provide a way to calculate the error rate.

Keywords—Feature extraction, lip analysis, lip detection, liprecognition, pattern recognition, SOM algorithm

I. 1.INTRODUCTION:

Biometric systems are widely used in identification and recognition applications, due to the bio-invariant characteristics of some specific structures such as fingerprint, face, and iris. Among these features, face recognition is able to work at a greater distance between the prospective users and the camera than other types of features. Yet, one critical issue of the face recognition system is that the system cannot work well if the target face is partially covered. Thus, considering a smaller part of a face for further identification /recognition can be an effective way to solve this problem.

Detecting lip contour with high accuracy is an important requirement for a lip identification system, and it has been widely discussed in former works. One of the studying directions considers the color information. Finally, the morphology was employed to smooth and binarize the image and then removed the noises to obtain the lip region. In, the images were converted into Caetano and Barone's chromatic color space. Afterward, the mean and the threshold were computed from the red channel of each pixel, and these were employed to separate the lips' and nonlips' regions. In, a new color mapping method, which integrated color and intensity information, was developed for the lips' contour extraction, and Otsu's thresholding was adopted to extract the binary result.

In fact, the influence incurring from the variability of the environment is the common problem for the aforementioned methods since the hue or the brightness is employed to distinguish the lips' and nonlips' regions.

II. 2.RELATED WORK:

Lip corners detection:

Grayscale value is a basic property of each pixel. Oneof the most common methods for feature extraction of themouth is the use of the grayscale. Although it works poorlyin lip segmentation, it functions well to detect lip corners.

Steifelhagen *et al*.[16] presented a method to detect lip cornersthat made use of grayscale value and edge etection. Rao andMersereau[17] also presented a method to detect lip cornersbased on statistics of grayscale value.

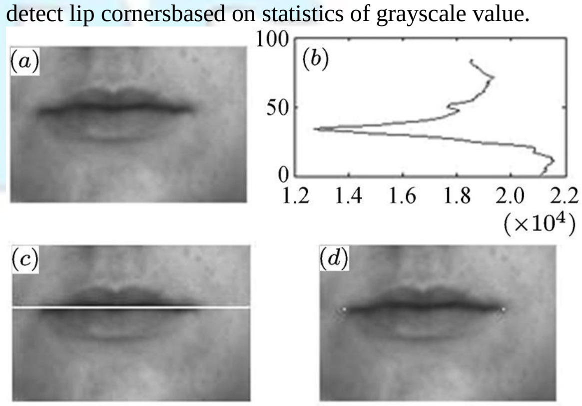


Figure. 1. Statistics of grayscale value based lip feature extraction.(*a*) Grayscale image; (*b*) Grayscale sum of eachrow; (*c*) The row with the minimum value of sum; (*d*)The lip corners (pointed by white points)

Lip corner can be detected by taking the sum of each row (Fig.1(*b*)) and finding the row with the minimum value

(Fig.1(*c*)). By examining the actual value of each pixel in the minimum row, and the rows close to it, one by one from the side to the middle, you can discover a lip corner candidate (Fig.1(*d*)) by setting a threshold. In this algorithm, the threshold is set at the average between maximum and minimum values for the row with the minimum value of sum of grayscale. After finding a candidate, check the neighbors of it to find out whether the candidate satisfies the condition of lip corner. If not, try to find another candidate.

The check strengthens the robustness of this lip corner detection. The lip corner can be detected precisely even with the presence of facial hair.According to the results of the experiments, this method can figure out different shape of the lips, even those with presence of facial hair (Fig.2).

Fig. 2. Examples of grayscale-value-based lip corners detection in different cases

In this study, we followed the classification of patterns of the lines on the lips proposed by Tsuchihashi, which is the most widely used classification in literature.10 It was found to have a clear description of nearly all of the commonly encountered lip patterns and was easy to interpret as follow:-

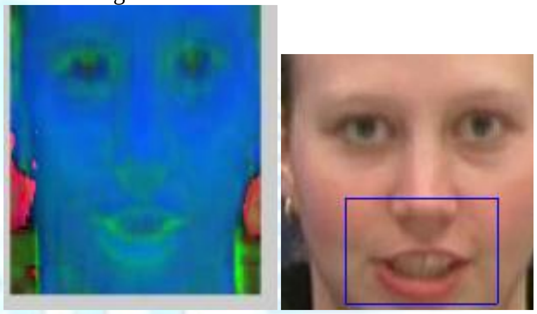
Type I: Clear-cut vertical grooves that run across the entire lips
Type I′: Similar to type I, but do not cover the entire lip
Type II: Branched grooves
Type III: Intersected grooves
Type IV: Reticular grooves
Type V: Grooves do not fall into any of the type I - IV and cannot be differentiated morphologically (undetermined).

The sex of the individual was determined as per the descriptions given by Vahanwala et al.6,7

Type I, I′: Patterns dominant - Female
Type II: Pattern dominant - Female
Type III: Pattern dominant - Male
Type IV: Pattern dominant - Male
Type V: (varied patterns) Pattern dominant - Male
Same patterns in all quadrants: Pattern dominant – Female.

Lip Localization

For the lip localization task, hue/saturation colour thresholding is implemented to differentiate the lips from the skin. The detection of the lip in hue/saturation colour is much easier owing to its robustness under wide range of lip colours and varying illumination conditions [11]. From the huesaturationimage, a binary image is then obtained by setting the threshold values, i.e. setting some specific threshold for hue and saturation. Lastly by employing morphological image processing, the lip region can be localized by finding the largest blob in the binary image. Lip Localisation process is shown below in Fig. 3.



III. METHODOLOGY:

Working progress of SOM:

Properties useful in exploring data

By virtue of its learning algorithm the SOM forms a nonlinear regression of the ordered set of reference vectors into the input space. The reference vectors form a two-dimensional ``elastic network" that follows the distribution of the data.

Ordered display.

The ordered nature of the regression justifies the use of the map as a display for data items. When the items are mapped to those units on the map that have the closest reference vectors, nearby units will have similar data items mapped onto them. Such an *ordered display* of the data items facilitates understanding of the structures in the data set. Kohonen (1981) was the first to propose using such displays to illustrate a data set.

The same display can be used for displaying several other kinds of information. One clear advantage of always using the same display is that as the analysts grow more familiar with the map, they can interpret new information displayed on it faster and more easily.

For example, the map display can be used as an *ordered groundwork* on which the original data variables, components of the data vectors, can be displayed in their natural order. Such displays have been demonstrated in

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Publication 2. The variables become smoothed locally on the display, which helps in gaining insight in the distributions of their values in the data set. Such displays are much more illustrative than, for instance, raw linearly organized statistical tables. It might also be useful to display the *residuals*, average differences of the variables from their smoothed values.

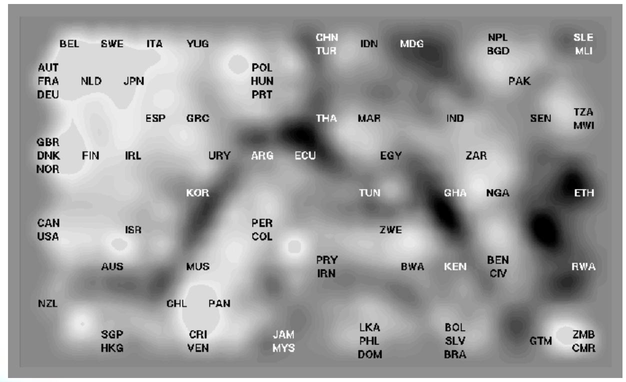
Visualization of clusters.

The same ordered display can be used for illustrating the *clustering density* in different regions of the data space. The density of the reference vectors of an organized map will reflect the density of the input samples [Kohonen, 1995c, Ritter, 1991]. In clustered areas the reference vectors will be close to each other, and in the empty space between the clusters they will be more sparse. Thus, the cluster structure in the data set can be brought visible by displaying the distances between reference vectors of neighboring units [Kraaijveld et al., 1992, Kraaijveld et al., 1995, Ultsch, 1993b, Ultsch and Siemon, 1990].

The cluster display may be constructed as follows [Iivarinen et al., 1994]. The distance between each pair of reference vectors is computed and scaled so that the distances fit between a given minimum and maximum value, after optionally removing outliers. On the map display each scaled distance value determines the gray level or color of the point that is in the middle of the corresponding map units. The gray level values in the points corresponding to the map units themselves are set to the average of some of the nearest distance values (on a hexagonal grid, e.g., to the average of three of the six distances toward the lower-right corner). After these values have been set up, they can be visualized as such on the display, or smoothed spatially.

The resulting cluster diagram is very general in the sense that nothing needs to be assumed about the shapes of the clusters. Most of the clustering algorithms prefer clusters of certain shapes [Jain and Dubes, 1988].

A demonstration of a display constructed using SOM is presented in Figure 5.



Missing data.

A frequently occurring problem in applying methods of statistics is that of missing data. Some of the components of the data vectors are not available for all data items, or may not even be applicable or defined. Several simple (e.g., Dixon, 1979) and more complex (e.g., Dempster et al., 1977) approaches have been proposed for tackling this problem, from which all of the clustering and projection methods suffer likewise.

In the case of the SOM the problem of missing data can be treated as follows: when choosing the winning unit by Equation 5, the input vector $\mathbf{x}$ can be compared with the reference vectors $\mathbf{m}_i$ using only those components that are available in $\mathbf{x}$. Note that none of the reference vector components is missing. If only a small proportion of the components of the data vector is missing, the result of the comparison will be statistically fairly accurate. When the reference vectors are then adapted using Equation 6, only the components that are available in $\mathbf{x}$ will be modified.

It has been demonstrated that better results can be obtained with the approach described above than by discarding the data items from which components are missing [Samad and Harp, 1992]. However, for data items from which the majority of the indicators are missing it is not justifiable to assume that the winner selection is accurate. A reasonable compromise, used in Publication 2, is to discard data items with too many (exceeding a chosen proportion) missing values from the learning process. Even the discarded samples can, however, be tentatively displayed on the map after it has been organized.

Note: Although the SOM as such can be used to explore incomplete data sets, some preprocessing methods may have problems with missing components of the input data items. For example, normalization of the data *vectors* cannot be done in a straightforward manner. Normalization of the variance of each component separately is, in contrast, a viable operation even for incomplete data sets.

Outliers.

In measurement data there may exist*outliers*, data items lying very far from the main body of the data. The outliers may result, for instance, from measurement errors or typing errors made while inserting the statistics into a data base. In such cases it would be desirable that the outliers would not affect the result of the analysis. This is indeed the case for map displays generated by the SOM algorithm: each outlier affects only one map unit and its neighborhood, while the rest of the display may still be used for inspecting the rest of the data. Furthermore, the outliers can be easily detected based on the clustering display: the input space is, by definition, very sparsely populated near the outliers. If desired, the outliers can then be discarded and the analysis can be continued with the rest of the data set.

It is also possible that the outliers are not erroneous but that some data items really are strikingly different from the rest. In any case the map display reveals the outliers, whereby they can either be discarded or paid special attention to.

Mathematical characterizations

Rigorous mathematical treatment of the SOM algorithm has turned out to be extremely difficult in general (reviews have been provided by Kangas, 1994; and Kohonen, 1995c). In the case of a discrete data set and a fixed neighborhood kernel, however, there exists a potential function for the SOM, namely [Kohonen, 1991, Ritter and Schulten, 1988]

$$E = \sum_k \sum_i h_{ci} \|\mathbf{x}_k - \mathbf{m}_i\|^2 , \qquad (7)$$

where the index c depends on the $\mathbf{x}_k$ and the reference vectors $\mathbf{m}_i$ (cf. Eq. 5).

The learning rule of the SOM, Equation 6, corresponds to a gradient descent step in minimizing the sample function

$$E_1 = \sum_i h_{ci} \|\mathbf{x}(t) - \mathbf{m}_i\|^2 \qquad (8)$$

obtained by selecting randomly a sample $\mathbf{x}(t)$ at iteration *t*. The learning rule then corresponds to a step in the stochastic approximation of the minimum of Equation 7, as discussed by Kohonen (1995c).

Note: In Equation 7 the index *c* is a function of all the reference vectors, which implies that it may change when the gradient descent step is taken. Locally, if the index $c = c(\mathbf{x}_k)$ does not change for any $\mathbf{x}_k$, the gradient step is valid, however.

IV. CONCLUSION

A lip recognition system with well-designed parameters has been proposed to surprisingly achieve recognition accuracy when only a partial part of the face is available. An additional advantage of handling various sizes of imported frames and different distances between the camera and the prospective users have been provided by applying Viola and Jones's face detection algorithm.Several stages have been involved in the proposed system, and the corresponding contributions have been organized as follows:The proposed FBF provides a faster processing speed than typical BF scheme when a greater filter size is required. The mouth corners detection scheme demands fewer iteration compared with former schemes in the literature, and thus, the overall recognition system can operate in real-time fashion. This proposed lip recognition is able to handle the critical issues when the shadow, the beard, or the rotation is involved. In this paper, the ultimate capability of the lips as a biometric
has been investigated

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