Gender Classification Based on Lip Colour

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Abstract. Much research has been reported in the field of gender classification through face recognition techniques making use of variation in skin textures and distances between the nose, eyes and mouth and so forth. However, to the best of our knowledge, no work has yet been done on recognition of males and females on the basis of lip colour. In this paper, we have proposed a two-stage methodology on the above subject. In the first stage, termed as the Lip Contour Extraction Stage, the colour contrast between the skin and the lip enables the lip contour extraction. The mask so obtained is made noiseless thus perfecting the contour. The next stage, termed as the Gender Classification stage, the extracted contour is classified for genders on the basis of pronounced variation in the hue and saturation values of the lip colour. These variations, though not discernible through the naked eyes, are analysed using training machines like SVM and Neural Network. The promising experimental results showing an overall accuracy of 85 % while an accuracy of 90% for Asian and 80% for White, for gender classification, can pave way to the future of lip recognition in Biometric systems.

Keywords : Gender Classification, Lip Recognition, model-based approach.

1 Introduction

Gender classification systems find varied applications ranging from criminology to biometric validation. These applications require characteristics recognition which is made possible using clearly discernible facial features like the eyes, the face structure and the texture of the skin between the two genders. One of these facial features is the lip region which can be used to distinguish between the two genders. The lip region is roughly the lower one third part of the face, comprising basically of the lips and region between the lips and nose. Apart from lip shape recognition systems, we believe that the applications of the lip region (such as lip based biometric identification) have not been investigated thoroughly.

Through this paper, we have investigated another arena of lip region application which is gender classification using lip colour. Though, the difference in the lip colour is not discernible through the naked eye, however, using the proposed model, a clear difference in the hue and saturation values of the lip colour has been observed. These observations have been mentioned in the later section of the paper.

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For an emphatic apprehension of the proposed model, the remaining part of this Section 1 is divided into the following sub-sections: Sub-section 1.1 incorporates the previous related works on the applications of lip region; Sub-section 1.2 brings forth such observations that have helped us in developing the proposed model after reviewing the prior works; Sub-section 1.3 spells out our contribution; Section 2 gives the framework for classification which is further divided into sub-sections 2.1 and 2.2 explaining the two stage methodology; Section 3 contains the experimental results while Section 4 consists of the discussion on the results and finally Section 5 draws the conclusion and future work on our model.

1.1 Related Work

There have been several approaches for Lip Contour Detection like [1], [2], [3], [4], [5] and for Gender Classification like [6], [7], [8]. Another study in lip colour has been for medical purposes as described in [9] and lip as a biometric as described in [10].

Lip Contour Detection has been carried out using several approaches, the two important ones being Active Contour Model (ACM) and Colour Segmentation. In the former approach as is done in [1] and [2], the lip contour is extracted by minimizing the associated energy while the latter approach as shown in [3], [4] and [5] presents a colour segmentation approach in which the red hue of the lip information is combined with Markov Random Field (MRF) model and then ACM has been used to get the perfect contours after the MRF modelling.

Study on gender classification has been done for facial features recognition and classification as well as for behavioural characteristics like that based on gait. Facial features like forehead, eyebrows, eyes, nose, lip and chin areas are easily differentiable for males and females. Methods like Principal Component Analysis for dimension reduction and Fisher Linear Discriminant algorithm for gender determination have been used in [7] and texture normalisation as intermediate methods for classification in [8]. Training machines like Support Vector Machine (SVM), Neural Network (NN), Adaboost and LDA have been used for classification purpose. [6] and [7] make use of the facial features, wherein the colour images are detected by converting the inherent RGB colour space into YCbCr colour space and then the lip region, mouth region and the nose regions are located. For gait based gender classification as done in [8], prior information is extracted from the psychological experiments which when combined with an automatic method increases the classification accuracy.

An altogether different application of lip colour has been studied in [9]. The Hue (H), Saturation (S) and Intensity (I) values of the various images are stored in the form of bins and then trained for five different lip colours namely pale red, light red, deep red, normal red and purple. The test images are then compared with the trained images and a good efficiency is obtained.

As mentioned in [10], the lip features have been confirmed as unique through studies by Yasuo Tsuchihasi and Kazuo Suzuki [11, 12]. Making use of Zemike and Hu moments as well as colour features, lips biometric system has been presented.

Thus, making use of Lip Contour Detection method as shown in [3], [4] and [5] and Colour based classification as shown in [9], a Gender Classification method can be developed to classify males and females on the basis of lip colour and shape. This very combination we have tried to achieve through our investigation and work.

1.2 Motivation

The following observations from the previous related works have led us to develop the proposed model for Gender Classification:

1. Lip Detection methods as shown in [3], [4], and [5] have led us to develop a method based on colour segmentation which has been explained in the later sections.
2. Gender Classification makes use of training machines like SVM, NN, LDA and Adaboost.
3. In [9], the HSI values of the lips are used to create bins and train and test the images using the aforementioned training machines. Using this method, the colour aspects of the lip can be used to distinguish the males and females.

Use of the lip features for classification purpose has the following advantages over the previous methods of gender classification, described in the prior section:

1. The lip region is generally visible; not hidden.
2. This type of classification is anatomical in nature; better accuracy is expected as against the behavioural type of classification.

Taking into consideration these advantages and the fact that this field of gender classification has not been studied well, we have proposed a system based on lip colour.

1.3 Contribution

We have developed a novel methodology for gender classification based on lip colour. Moreover, to our knowledge, the lip contour detection method used in this paper is a novel method as well. The method, which is a prerequisite to classification, creates a mask by Hue selection of the image and then removing the noise from the mask by using the method as explained later in this paper. The Gender classification stage makes use of the H, S, and I values of the extracted contour. Finally the trained images are compared with the test images and the likewise results are obtained. The highlight of this approach lies in its simplicity and cogent efficiency. Our contributions include:

1. Development of a colour based segmentation approach for lip contour extraction using the Hue values of the region of interest (ROI).
2. Development of a colour specification model for classification based on lip colour for both males and females.

The proposed method of lip contour detection is similar to [3] and [4]. The contour detection method, though a prerequisite, can be implemented as a plug-in, i.e. the prior methods can be used for the same purpose but with a varied efficiency. The final stage of gender classification only depends on the mask obtained from the contour; hence better the contour, more the accuracy.

2 Framework for Classification

The following assumptions are taken into account for classification purpose:

1. The ROI is the lower one third portion of the face;
2. The mouth of the subject is closed; teeth and tongue are not visible.
3. The race and age of the person are known which are critical in determining the efficiency of the proposed model.

According to the two-stage model we have proposed, the first stage as the Lip contour Detection stage and the second stage as the Gender Classification stage, the latter being further sub-divided into two stages viz. the Colour Specification and Testing of Images. The last sub-stage uses the three training machines for testing and training viz. Support Vector Machine (SVM), Neural Network (NN) and Perceptron respectively.

The stages are described in detail as follows:

2.1 The Lip Detection Stage

In this stage (as shown in Figure 1), the input is the image of the region of interest and the output is the mask of the image which is then used for classification purpose. The intermediate stages are Lip Region Masking and Noise Removal. The intermediate stages are explained as follows:

1. Lip Region Masking: This method is used to calculate the hue values of the inherent RGB and they are normalized. The hue values greater than 0.5 are folded back onto 0.5 – 0 range and then the values between 0 and 0.04 are extracted to create a mask (which has noise). Folding is done to shift right half region of the hue to 0 as lip pixels are in both the left and right extremes of hue range. The next stage is used to remove the noise and get a perfect contour for classification.

   The algorithm is as follows:

```
Input: RGB Mouth Region Image.
Step 1: Convert RGB image to HSI Color space.
Step 2: If Hue value (H) > 0.5 Then H = H – 2(H-0.5)
Step 3: If H < 0.04 Then H = 1
        Else H = 0
Output: H that is Lip Region Mask (with Noise)
```

2. Noise Removal: In this stage, all the single non-connected pixels in the image are filled and then the region with the largest area is used as contour while the rest of the regions are discarded.

The algorithm is as follows:

```
Input: H that is Mask from lip region masking stage
Step 1: Fill all not connected, single pixels in mask
Step 2: Label all connected regions extracted in mask
        with Natural numbers, i.e. make value of all
        pixels in that region equal to label number (#).
Step 3: A# = area for # Labelled region; X = # of max(A# ∀ #)
Step 5: For all regions in mask H If # == X Then # = 1
        Else # = 0
Output: H that is Lip region mask (without noise)
```

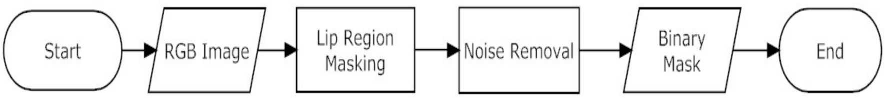

Fig. 1. Lip Contour Extraction

Finally the mask of the lip region is obtained and sent as an input to the next stage i.e. Gender Classification stage as shown in Figure 2.

2(a). Original Image **2(b).** Imageafter Stage 1 **2(c).** Image after Stage 2 **2(d).** Mask overlaid on original

Fig. 2. Mask Obtained after Lip Contour Detection Stage

2.2 The Gender Classification Stage

The mask of the image obtained in the first stage is an input to the first sub-stage, i.e. Colour Specification. The output of this stage is colour specific bins which are then sent to the second sub-stage which tests the given images. Training and testing are done via three training machines, SVM, Neural Network and Perceptron. The various sub-stages are explained as below:

Colour Specification. In this sub-stage (refer to Figure 3), formation of bins of H, S and I is taking place. These bins are then sent to each of the training networks.

$$H = \{\theta \text{ if } B<=G,\ 360 - \theta \text{ if } B>G\} \tag{1}$$

where $\theta = \cos^{-1}(((0.5*(R-G)+(R-B))/((R-G)^2+((R-B)(G-B))^{1/2})$

$$S = 1-(3/(R+G+B))*(\min(R,G,B)) \tag{2}$$

$$I = 1/3*(R+G+B) \tag{3}$$

H, S and I values are calculated according to equations (1), (2) and (3). These values are then normalised and the single matrices of the three values of size 13, 13 and 17 respectively are concatenated to form a bin of size 43 for each image. These bins are then sent to each of the training machines aforementioned as inputs and are trained according to their gender.

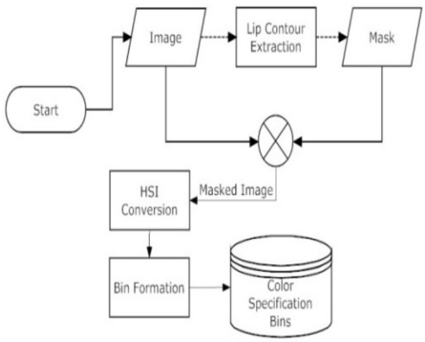

Fig. 3. Colour Specification Stage-H, S, I values of the lip contours obtained are sent to the Bin Formation process and trained according to the respective genders

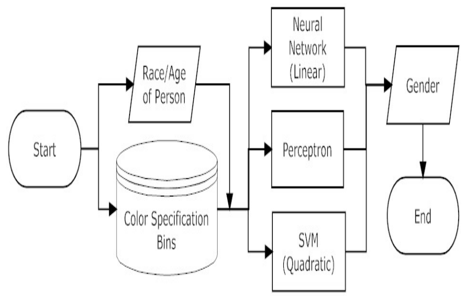

Fig. 4. The Testing Stage-For testing, the bins are also trained according to race and age of the subjects and then trained according to the respective genders

Testing of Images. The trained database for both colour specification and lip shape detection is then used to test the images using the aforementioned training machines as shown in Figure 4.

3 Experimental Results

The implementation of the algorithm is carried out on AMD Athlon™ 2.4 GHz Processor, 4 GB RAM, Windows 7 Ultimate in MATLAB® Release 2010a. The algorithm is implemented on 125 subjects taken from FERET database [13] since it is one of the largest database of facial images (1199 individuals), hence appropriate for our experimentation. It consists of images collected between August 1993 and July 1996. However, only the images taken in 1994 of the 125 subjects are processed since the particular database has better lighting conditions, thus befitting our algorithm. The dataset used for the experimentation consists of only those images in which the subjects are facing front towards the camera. The dataset also contains information about the age and race of the subjects. The training images are sent to the Colour Specification Stage for formation of bins as explained in the previous section. The bins formed in this stage are trained using SVM, Neural Network and Perceptron. As mentioned in the earlier sections, there is a significant difference in the hue and saturation of the lip colour of males and females belonging to White and Asian races. Following results indicate this difference by plotting the number of pixels occupied by each bin versus the range of each bin for both genders and races:

1. *Hue and Saturation variation in lip colour of males and females belonging to Asian race.*

From Figure 5, it is evident that the hue values of the both genders are centralized in the bins 0.04 – 0.12 which is around the red region. However there is a difference in the percentage of the number of pixels occupied by the lip colour of respective genders. While from Figure 6, the number of pixels occupied by both the genders has a definite pattern.

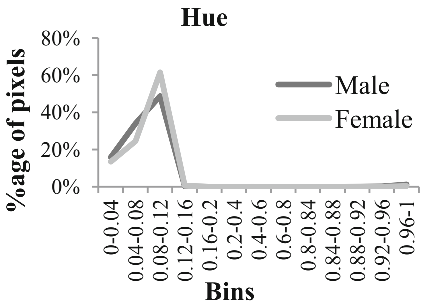

Fig. 5. Hue Variation in lip colour of both genders (Asian Race)

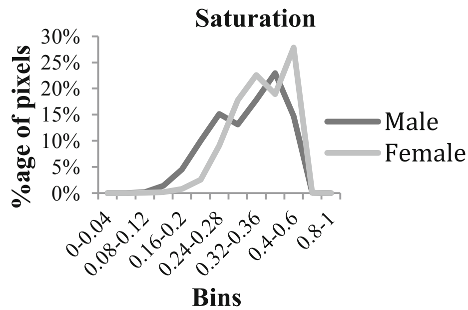

Fig. 6. Saturation Variation in lip colour of both genders (Asian Race)

2. *Hue and Saturation variation in lip colour of males and females belonging to White race.*

From Figure 7, it is evident that the hue values of the both genders are centralized in the bins 0.04 – 0.12 which is around the red region. However, there is no significant distinction between the two.

While from Figure 8, the number of pixels occupied by both the genders has a definite pattern different from the Asian race.

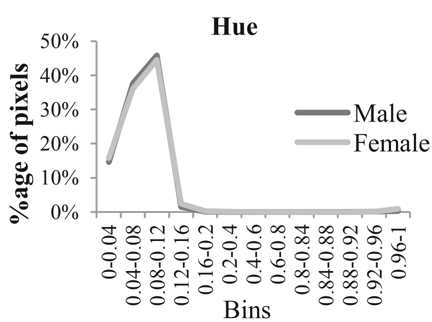

Fig. 7. Hue Variation in lip colour of both genders (White Race)

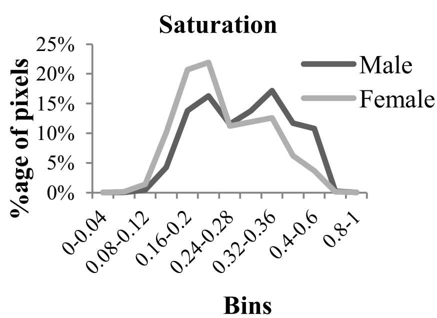

Fig. 8. Saturation Variation in lip colour of both genders (White Race)

Thus making use of the aforesaid distinct variations, the test images are tested for the following cases:

1. Race and Age are taken as the classification parameters:
   a) The age and race of the subject are not known;
   b) The race of the subject is considered while the age is not known;
   c) The age of the subject is considered while the race is not known;
   d) The race and age of the subject, both are considered.
2) Different kernel functions in SVM are taken as classification parameters:
3) Different layers and neurons in Neural Network are taken as classification parameters:

On the basis of the aforementioned cases, the following results are obtained:

I. Race and Age are taken as the classification parameters

a) The age and race of the subject are not known*:*

Fig 9 shows the accuracy of the various training machines i.e. SVM, NN and Perceptron while the race or the age of the subjects is unknown. Time taken for testing is 51.55 seconds.

b) The race of the subject is considered while the age is not known*:*

Fig 10 shows the accuracy of the various training machines i.e. SVM, NN and Perceptron when the race of the subject is known, however the age is not known. The various races taken into consideration were Asian, Hispanic, White and Middle-Eastern. Time taken for testing is 1 minute and 14.14 seconds.

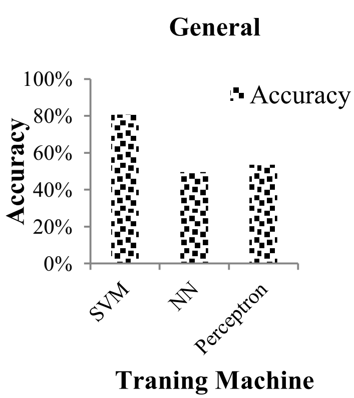

Fig. 9. Gender Classification (race/age not known)

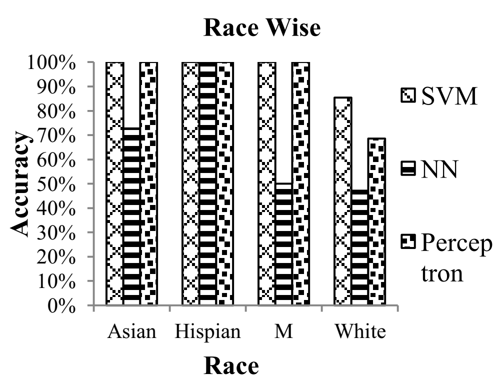

Fig. 10. Gender Classification (race is known)

*M – Middle Eastern

c) The age of the subject is considered while the race is not known*:*

Fig 11 shows the accuracy of the various training machines i.e. SVM, NN and Perceptron when the age of the subject is known, while race is not known. The various age groups taken into consideration were 15-24, 25-34, 35-44 and 45-54. Time taken for testing is 53.58 seconds.

d) The age and race of the subject , both are considered:

Fig 12 shows the accuracy of the various training machines i.e. SVM, NN and Perceptron when both the race and the age of the subject are known. Time taken for testing is 51.51 seconds.

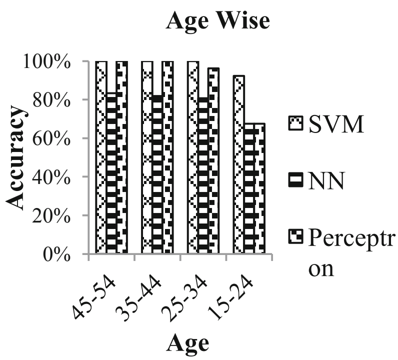

Fig. 11. Gender Classification (age is known)

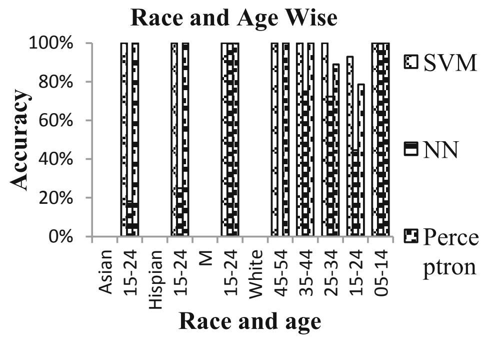

Fig. 12. Gender Classification (age/race known)

II. Different Kernel Functions in SVM are taken as classification parameters

Fig 13 shows the accuracy with the different types of Kernel functions in SVM when race of the person is not known while Fig 14 shows the accuracy when the race of the person is known. The time taken is 28.32 seconds for the first while 1 minute 14 seconds for the second result.

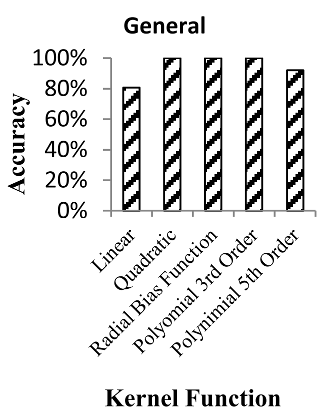

Fig. 13. Gender Classification using different Kernel Function (race not known)

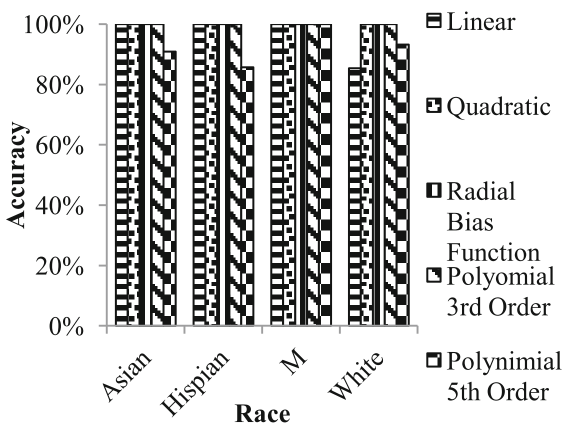

Fig. 14. Gender Classification using different Kernel Function (race is known)

III. Different number of layers and Neurons in Neural Network are taken as classification

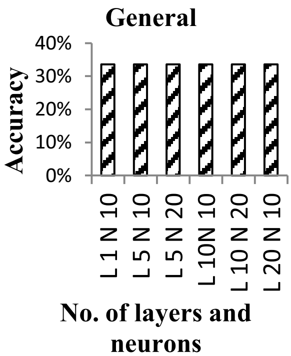

Fig. 15. Gender Classification with different layers and neurons (race not known)

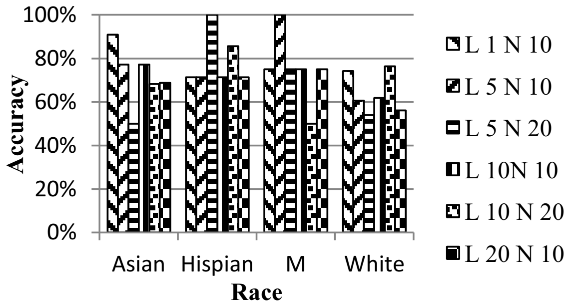

Fig. 16. Gender Classification with different layers and neurons (race known)

Figures 15 and 16 show the accuracy of classification with different number of layers and neurons when the race is not known and when the race is known, respectively.

- Where L is the number of layers and N is the number of neurons

4 Discussion

The experimental results as presented in the previous section can be summarised as follows:

1. SVM shows the highest accuracy while classifying with or without the knowledge of age and race as against NN and Perceptron.
2. While making use of different Kernel functions in SVM, Quadratic, Radial Basis (RBF) and 3rd order Polynomial have the maximum accuracy both while classifying with or without the knowledge of age and race as against the other kernel functions.
3. In case of Neural Network based classification, almost equal and low (less than 35%) accuracy is obtained for different layers and different number of neurons, when the race is not known. However, very good accuracy is obtained when the race is known. Increasing the number of neurons and layers to an optimum value enhances the accuracy of classification.

5 Conclusion

In this paper, we have presented a novel method for gender classification based on lip colour. This method makes use of Colour Segmentation based Lip Contour Detection which has been used to classify males and females on the basis of lip colour. Experimental Results indicate that the accuracy as well as efficiency of classification increases if the race and age of the subject is taken into consideration. Thus, our assumption that race and age of the subject should be a prerequisite has been confirmed.

However, in order to make our methodology more effective and useful for automation in the future, we address the following issues. Firstly, after analysis, it was found out that the model works for only a few races i.e. Asian, Hispanic, Middle-Eastern and White. We thus, aim to extend the proposed methodology to recognise the subjects irrespective of their race. Secondly, in our model, the lip colour feature is only used for classification. However, we intend to widen our research on gender classification based on other lip features such as the shape and texture, which can further increase the accuracy for classification. Moreover, the images used for experimentation are static images. We, thus seek to develop a model that has a real-time database having good resolution lip region as the region of interest. We, thus, hope to increase the efficiency of the model once the aforementioned issues are resolved.

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