Efficient Skin Region Segmentation using Low Complexity Fuzzy Decision Tree Model

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Abstract— We propose an efficient skin region segmentation methodology using low complexity fuzzy decision tree constructed over B, G, R colour space. Skin and nonskin training dataset has been generated by using various skin textures obtained from face images of diversity of age, gender, and race people and nonskin pixels obtained from arbitrary thousands of random sampling of nonskin textures. Compact fuzzy model with very few numbers of rules allow to raster scan consumer photographs and classify each pixel as skin or nonskin for various face and human detection applications for embedded platforms.

Keywords—— **Fuzzy decision trees, Skin Segmentation**

I. INTRODUCTION

Skin-like region segmentation has been utilized as a pre-processing step for various face and human detection and tracking applications [1-6]. Colour space-based models act as efficient approaches for quickly identifying the skin-like regions before performing complicated steps like face and body detection and tracking. Various colour space-based approaches have been proposed by researchers [7-11]. However, skin region segmentation for embedded systems porting needs separate attention because of processing limitations of the devices. Further, applications in to consumer electronics products should work with very good time-accuracy trade-off for deployment into market and success of the products. In this paper, we propose the skin-like region segmentation approach specifically for embedded systems applications with high accuracy and fast processing time as the main target. We have used fuzzy decision tree (FDT) induced over skin and non-skin training patterns. By the suitable selection of learning parameters, a compact FDT model has been generated which segments skin-like regions of consumer images in fraction of seconds.

This paper is organized as follows. In Section II, we describe the skin-like region segmentation approach proposed in this paper along with the brief description of FDT and specifically, FDT induced for the skin segmentation problem. Computational experiments and results have been discussed in Section III. Section IV concludes the paper.

II. PROPOSED APPROACH FOR SKIN REGION SEGMENTATION

A. The Proposed Approach

Our aim is to build an efficient human object presence algorithm and localize at least one face for categorization of consumer images into portraits and non portraits for Auto Album generation. The target processor is ARM 11 core, 500 MHz clock with 256 MB DDR2 memory and two 32 KB cash memory. For human object detection, we have added skin segmentation as a pre-processing step followed by the other algorithms. For the induction of rule-based model for skin segmentation we have used fuzzy decision trees trained over skin and nonskin samples. We have collected skin dataset by randomly sampling B,G,R values from face images of various age groups (young, middle, and old), race groups (white, black, and asian), and genders obtained from FERET database and PAL database [12,13]. Total learning sample size is 51444; out of which 14654 is the skin samples and 36790 is nonskin samples. This makes our training Db is of the dimension 51444 * 4 where first three columns are B,G,R (x_1, x_2, and x_3 features) values and fourth column is of the class labels (decision variable y). On this Db we have developed fuzzy decision tree using fuzzy ID3 induction algorithm. A brief explanation of fuzzy decision trees and fuzzy ID3 algorithm is given below.

B. Fuzzy Decision Trees

Fuzzy decision trees are powerful, top-down, hierarchical search methodology to extract easily interpretable classification rules [14, 15]. Fuzzy decision trees are composed of a set of internal nodes representing variables used in the solution of a classification problem, a set of branches representing fuzzy sets of corresponding node variables, and a set of leaf nodes representing the degree of certainty with which each class has been approximated. We have used our own implementation of fuzzy ID3 algorithm [14,15] for learning a fuzzy classifier on the training data. Fuzzy ID3 utilizes fuzzy classification entropy of a possibilistic distribution for decision tree generation.

Before induction of fuzzy decision tree, training patterns pertaining to three input attributes have been clustered using fuzzy *c*-means clustering algorithm [16] into five fuzzy clusters. These fuzzy clusters have been approximated as a Gaussian membership function using the dispersion factor 0.2 [17]. Plot of fuzzy membership functions after Gaussian membership estimation is shown in Fig. 1 below.
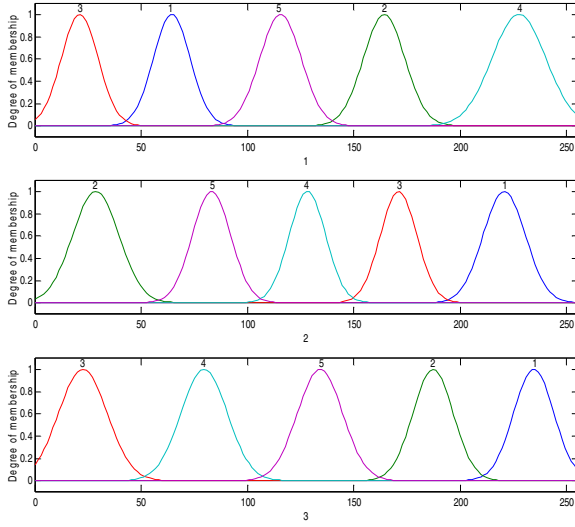
Fig. 1 Gaussian membership functions for B,G,R planes

Figure 2 shows fuzzy decision tree using fuzzy ID3 algorithm for the skin-nonskin classification problem. We have taken leaf selection threshold 0.75. In Fig. 2, root node is represented by $R = x_3$. There are total seven leaf nodes shown by bold dotes. Children nodes have been terminated as leaf nodes because their respective certainty thresholds (all β) are greater than 0.75. β_{mS} and β_{mN} are prediction certainties of mth leaf node with respect to class skin and nonskin, respectively.
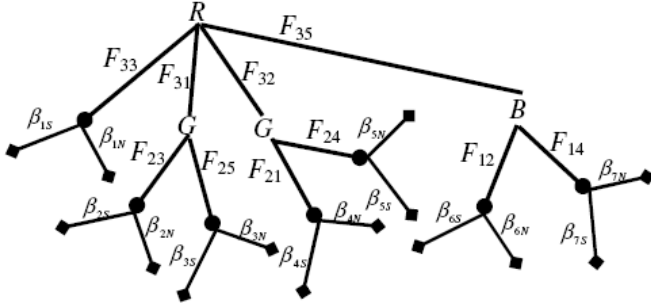

Fig. 2 Fuzzy decision tree for skin-nonskin classification problem

Certainty coefficients of all the leaf nodes are given as below :

$$\begin{bmatrix} \beta_{1S} & \beta_{1N} \\ \beta_{2S} & \beta_{2N} \\ \beta_{3S} & \beta_{3N} \\ \beta_{4S} & \beta_{4N} \\ \beta_{5S} & \beta_{5N} \\ \beta_{6S} & \beta_{6N} \\ \beta_{7S} & \beta_{7N} \end{bmatrix} = \begin{bmatrix} 0.00 & 1.00 \\ 0.92 & 0.08 \\ 0.00 & 1.00 \\ 0.00 & 1.00 \\ 0.94 & 0.06 \\ 0.00 & 1.00 \\ 0.00 & 1.00 \end{bmatrix}.$$

Certainty coefficients can be calculated by standard subsethood formula [14]. For example, β_{2S} can be calculated by

$$\frac{\sum_{i=1}^{n} \left(\mu_{F_{12}}(x_{1i}) \times y_i \right) \times \left(\mu_{F_{72}}(x_{7i}) \times y_i \right)}{\sum_{i=1}^{n} \mu_{F_{12}}(x_{1i}) \times \mu_{F_{72}}(x_{7i})},$$

where n is total number of patterns, x_{ji} is i^{th} pattern of jth feature, and $\mu_{F_{jk}}(x_{ji})$ is degree of membership of x_{ji} to k^{th} membership function on j^{th} feature.

Using this FDT, patterns are classified by starting from the root node and then reaching to one or more than one leaf nodes by following the path of degree of membership greater than zero. One can use either *min-max-max* or *product-product-sum* [14] reasoning mechanism over extracted rules to calculate the degree of certainty with which an arbitrary pattern can be classified to one class. In this paper, we have used the later one. The *product-product-sum* reasoning mechanism consists of the following three steps:

a. For the operation to aggregate membership values of fuzzy sets of node genres along the paths, the product is adopted.

b. For the operation of the total membership value of the path of fuzzy evidences and the certainty of the class attached to leaf-nodes, also the *product* is adopted.

c. For the operation to aggregate certainties of the same class from different paths, the *sum* is adopted.

To put these steps in mathematical notations, let us consider that there are total of M paths of fuzzy decision tree and total number of attributes on m^{th} path is P_m. With this, firing strength of mth path is given by

$$\mu_m = \prod_{j=1}^{P_m} \mu_{mj}(x_{mj}), m = 1, ..., M, \qquad (1)$$

where x_{mj} is j^{th} feature on m^{th} path. Prediction certainty of class-1 and class-2 by m^{th} path is given by

$$\beta_{m1} \times \mu_m, \beta_{m2} \times \mu_m. \qquad (2)$$

Finally, aggregate the predictions certainties of class-1 and class-2 from different paths using the following formulas.

$$\hat{d}^1 = \sum_{m=1}^{M} \beta_{m1} \times \mu_m$$
$$\hat{d}^2 = \sum_{m=1}^{M} \beta_{m2} \times \mu_m. \qquad (3)$$

The predicted class $\hat{y}$ is given by *winner-takes-all* logic, *i.e.*,

$$\hat{y} = \max_{1 \leq q \leq Q} \hat{d}^q. \qquad (4)$$

Centre and standard deviation matrix associated with each of the path of fuzzy decision tree are given below :

$$\mathbf{C} = \begin{bmatrix} 0 & 0 & 22.45 \\ 0 & 170.97 & 234.49 \\ 0 & 82.95 & 234.49 \\ 0 & 220.65 & 187.17 \\ 0 & 128.06 & 187.17 \\ 164.17 & 0 & 133.97 \\ 227.50 & 0 & 133.97 \end{bmatrix}; \mathbf{S} = \begin{bmatrix} 0 & 0 & 11.40 \\ 0 & 8.58 & 9.46 \\ 0 & 9.02 & 9.46 \\ 0 & 9.93 & 9.46 \\ 0 & 8.58 & 9.46 \\ 9.75 & 0 & 10.63 \\ 12.66 & 0 & 10.63 \end{bmatrix}.$$

III. Computational Experiments

We have performed various computational experiments on PC and on embedded hardware with specifications given in Section II above. Our ten fold cross validation average performance is 94.10 %. The average confusion matrix is given below :

$$\mathbf{conf} = \begin{bmatrix} & \text{Skin} & \text{Nonskin} \\ \text{Skin} & 98.09 & 1.90 \\ \text{Nonskin} & 7.48 & 92.51 \end{bmatrix}.$$

Above results shows that the algorithm is highly efficient in declaring actual skin as skin, where as confusion of almost 7.5 % is involved for nonskin segments. We have executed the proposed algorithm for various consumer images. Some of the skin segmented and actual images are shown below for illustration. To report the timing performance all the images have been scaled to standard 640 * 480 (*i.e.*, VGA size) resolution.
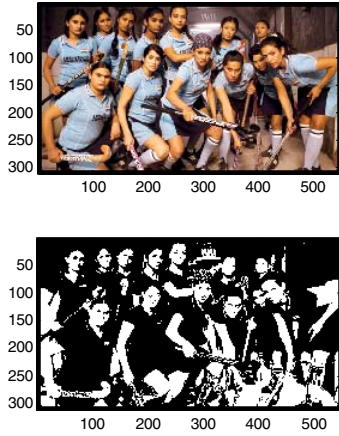

Fig. 3 Result on Chak De India group photograph. Timing 250 mSec.

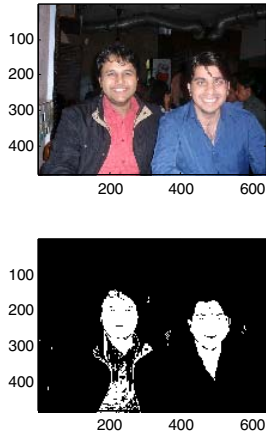Fig. 4 Result on Asian consumer image. Timing 250 mSec.

IV. Conclusions

In this paper, we have proposed B,G,R colour-based skin segmentation approach using fuzzy decision tree. Very compact FDT model using just seven leaf nodes (*i.e.*, fuzzy rules) makes it very efficient for application into embedded devices. Further, each fuzzy rule makes use of at the most two attributes which makes the algorithm application fast enough for the real world applications into products.

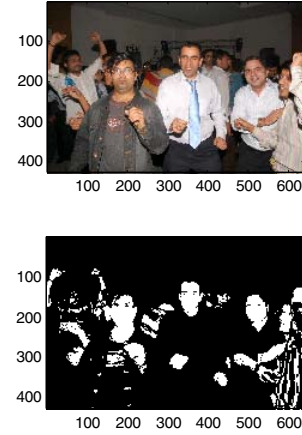Fig. 5 Result on East Asian consumer image. Timing 216 mSec.

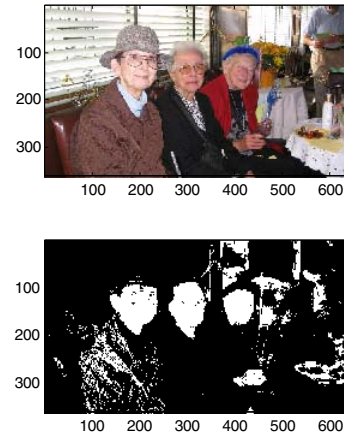Fig. 5 Result on party photograph with varying illumination. Timing 216 mSec.

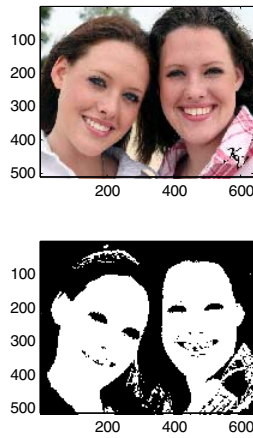Fig. 6 Result on white race ladies. Timing 237 mSec.

Fig. 7 Result on white race ladies portrait photograph. Timing 250 mSec.
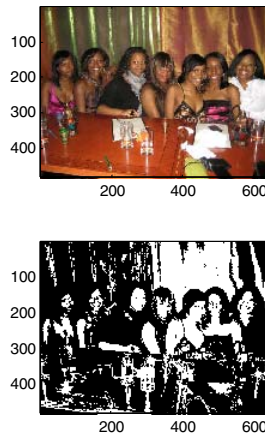

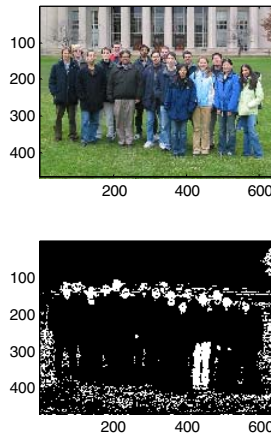Fig. 8 Results on Black ladies with illumination. Timing 208 mSec.

Fig. 9 Multiple faces with diversity of age, race, gender. Timing : 250 mSec.

It is clearly evident from the results and timing information that at most VGA image takes 250 mSec for the skin segmentation. As a further research, we plan to include eye-lips-nose localization algorithm for complete face detection application and then detection of orientation of portrait images.

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