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FUSING OFFLINE TRAINED MODEL FOR HUMAN SKIN SEGMENTATION

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Abstract-Graph cuts have been an emerging tool for many applications. In this paper, the research work is based on image segmentation for detecting skin pixels using the two well-known machine learning classifiers; neural networks and random forests. In order to improve the efficiency, we then merge the results of the two classifiers using graph cuts technique. We compare our results to that of the previous work, where the classifier used was J48 (Decision Trees) graph cut based merged result which shows that if proper weights are adjusted, the performance can be increased by merging different classifier.

1. INTRODUCTION

Image or skin segmentation is used as one of the many pre-processor stages for most of the applications [1, 2]. The objective of image segmentation is to classify an image into different regions. Skin based image segmentation is to recognize pixels in an image that corresponds to human skin.

The availability of skin and non-skin pixel is typically perceived by transforming a pixel into some defined color space. After this transformation a skin color based trained classifier is used to define a boundary for it. The main difficulty in finding a skin pixel is the existence of skin-like color pixel in the background. The other constraint that takes into account while finding a skin pixel is the changing illumination conditions. Color based skin detection [3] is one of the most commonly used techniques for detecting skin region in which a fixed boundary is defined for each color component. The most commonly used color spaces are RGB, HSV [4] and YC_bC_r [5] etc. Color constancy is another important factor while detecting skin pixel.

Machine learning has been a wide area of research from a last few decades [6]. The different algorithms for machine learning include Bayesian network, Multilayer perceptron, random forests, fuzzy based skin detection [7] and self-organizing map [8]. In order to train these machine learning algorithms, training data is required so that these algorithms may generalize from their experience. In order to make the machine learning algorithms learn from data, two different approaches exist; supervised learning and non-supervised learning [9, 10].

Graph cuts are one of the main topics of research in the area of image segmentation [11]. Graph cuts involve geometric analysis. The other reason for using graph-cuts is that, it minimizes both binary and non-binary energies. A cut on a graph is just like a hyper surface in multidimensional (N-D) space [12]. Graph cuts are also a useful multidimensional optimization tool in graphics and vision.

The color space used in our approach is the RGB color space. Random forests [13] and Multilayer perceptron or neural networks [14] are the two machine learning algorithms that are used in our experiments, due to its efficiency and performance as compared to other approaches. The main objective, of this work is to combine these two results and then analyze the final results. The combined results show more accuracy, and are more efficient.

2. SEED BASED APPROACH

Most of the skin detection through graph cuts uses seed based approach. Seed based approach uses two types of weights i.e. neighborhood weight and pixel weight, Fig. 2.1.

It depends on two parameters; one is window size and another sampling rate. We use 21x21 window size whereas the sampling rate is 0.3.

$$W_{q,r} = \left(e^{-\frac{\|c_q - c_r\|^2}{\sigma}} \right) \cdot \frac{1}{\| q - r \|}$$

The terminal nodes help in incorporating the pixels information from the local or universal seed/template. Due to the connection of pixels with the terminal nodes, background and foreground values can be distinguished.

The probability for a pixel being foreground/background is calculated using Bayes theorem,

$$p(B \mid c_q) = \frac{p(c_q \mid B)\, p(B)}{p(c_q)}$$

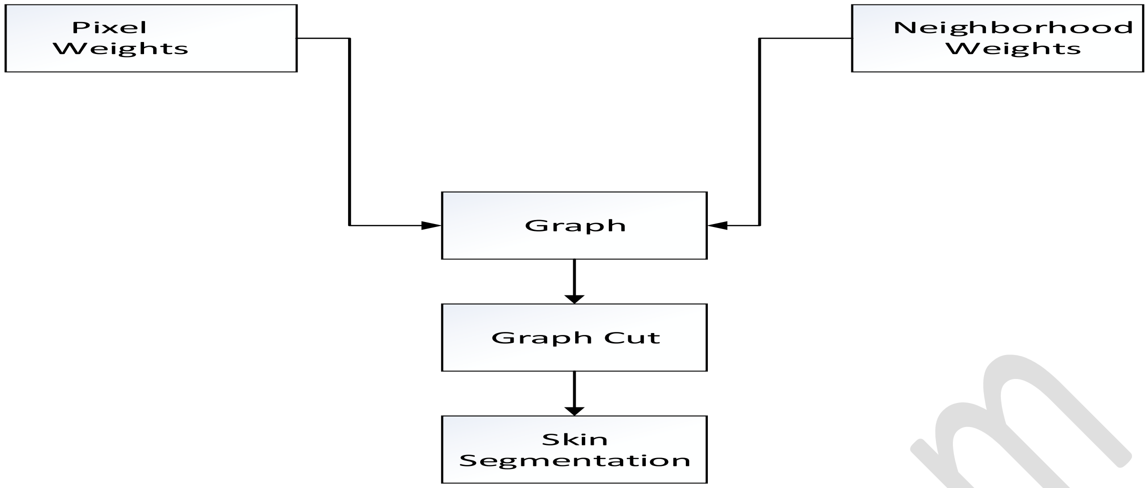

Fig. 2.1 The seed Based Approach for Skin Segmentation

Here *B* represents the background weight and $c_q = (c_L, c_a, c_b)$ stands for a vector in R^3 of L*a*b values at pixel q.

3. FUSION METHODOLOGY

The fusion strategy of the two classifiers is accomplished by using graph cuts technique. The local skin information and offline model interrogation (Multilayer Perceptron and Random Forests) is being used. First the classifiers i.e. multilayer perceptron and random forests are learned. The learned model helps in augmentation by using the seed based information, in case when no local information is present. If this does not detect skin then seed based information is loaded from which we compute the foreground histogram. A graph is created using the foreground/background and neighborhood weights.

The best possible combinations for fusion we can have from the skin and non-skin information are:

- Using background pixels information from multilayer perceptron and foreground pixels information from random forests.
- Using background pixels information from multilayer perceptron and foreground pixels information from multilayer perceptron.
- Using background pixels information from random forests and foreground pixels information from multilayer perceptron
- Using background pixels information from random forests and foreground pixels information from random forests.

4. RESULTS

In this section the results of individual classifier and fusion has been discussed.

Fig. 4.1 Random Forests Results

Fig. 4.2 Multilayer Perceptron Results

Fig. 4.3 Different Classifiers' Fusion Result

As can be seen from the above figures that the individual results contains information from background as well whereas the fusion of classifiers has removed some of the background information and added the foreground information, Fig.4.4.

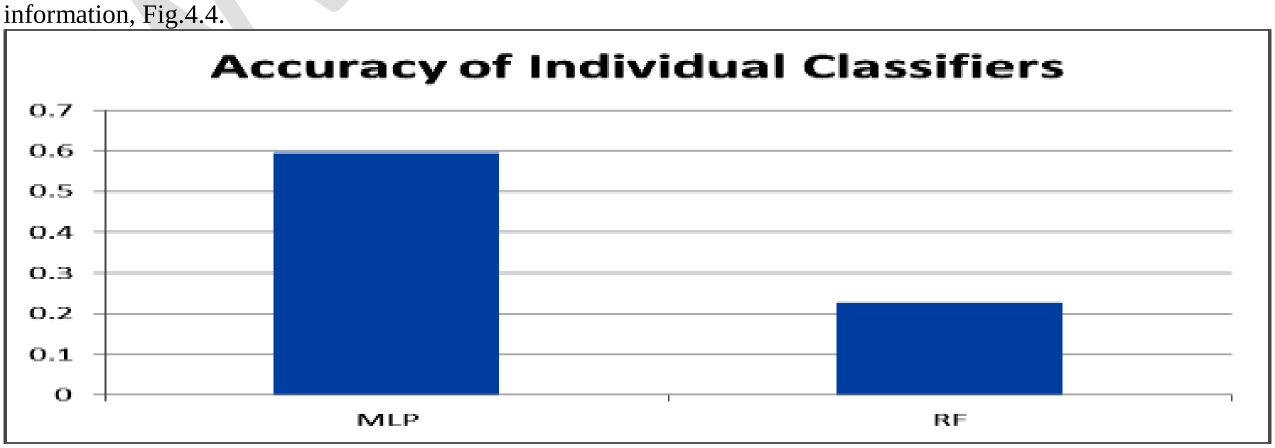

Fig. 4.4 Accuracy of Individual Classifiers

Fig. 4.5 shows the accuracy rates of independent classifiers i.e. 0.2284 for random forests and 0.5950 for multilayer perceptron.

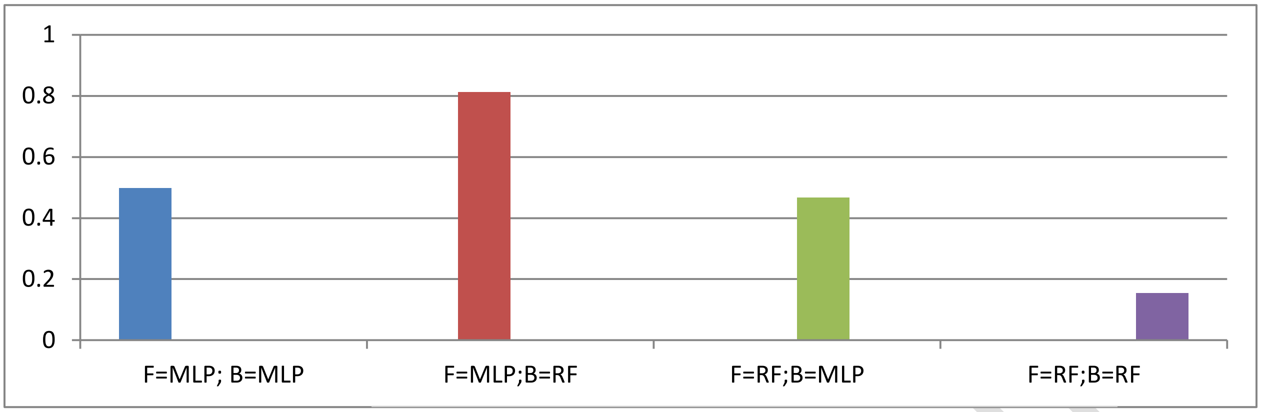

Fig. 4.5 Accuracy Rates of Different Possible Combinations of Probabilities of Classifiers

This graph clearly illustrates the maximum accuracy rates of different classifiers probabilities i.e. by merging the individual classifiers probabilities, not only the merged results of MLP and Random Forest is maximum than the other three combinations but also greater than the individual classifiers accuracy rates i.e. 0.2284 for random forests and 0.5950 for multilayer perceptron.

CONCLUSIONS

As an individual classifier multilayer perceptron shows better accuracy than the random forests. Therefore, it can be concluded that multilayer perceptron classifiers are well suited for pixel based skin detection.

The local skin information while using an offline trained model has been used, that increased the efficiency of the overall mechanism for the processing of random images using graph cut. A basis for combining a spatial and non-spatial data has been developed successfully in this paper.

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