Frequential and color analysis for hair mask segmentation

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ABSTRACT

In this paper, we present an automatic method for hair segmentation. Our algorithm is divided into two steps. Firstly, we take information from frequential and color analysis in order to create binary masks as descriptor of the hair location. Secondly, we perform a 'matting treatment' which is a process to extract foreground object from an image. This approach is based on markers which are initialized from the fusion of frequential and color masks. At the end of this process, we segment the hair from the matting treatment result. Results are evaluated using semi-manual segmentation references.

Index Terms— Hair segmentation, Face recognition, Matting processing

1. INTRODUCTION

Hair is an important feature of human appearance. *Figure 1* shows the importance of hair in face recognition. We achieve to recognize the two American politicians only thanks to their hair style. Indeed internal facial features of Bill Clinton have been replaced to Al Gore's face [1].

Fig 1. "*Presidential illusion*" (from [1])

Hair detection, analysis and use have not been deeply explored in the face recognition processing. Most of existing methods are based on the study and characterization of the internal features of the face. Hair may also provide a cue for identification process, at least it can facilitate the process by reducing possible matches. In case of identity verification, the hair features evaluation will be even more useful because it will bring more parameters in a description of a person.

Using hair in face recognition was considered until recently as a non stable parameter because hair aspect can be easily changed. However even if people can changed their appearance significantly by changing their hair style, the majority of the population keep a usual and classic hair appearance. Only few people may change their hair style and less of 2% do it regularly.

It appears that analysis and automatic segmentation of hair are not easy. Hair style can be very different from one person to another one. The two main characteristics are listed below.

 - **The presence and the distribution of the hair.** Unlike internal facial feature like eyes and mouth, people don't have always hair. Hair can be partially or totally absent (shaved and bald person). Hair can also appear split in several parts (ponytail mats, etc).

 - **The hue of hair.** Hair doesn't have a uniform color especially for clear color where roots and locks can be very different. The color of the hair is moreover hard to define with new trends. The current fashion of using dye leads to find hair with unnatural colors such as blue, green or violet... or non uniform dye with highlights.

Recently, hair analysis has been developed in scientific literature hence only few publications deals with this topic. The most relevant paper was recently published by Yacoob and Davis [2]. Their approach is based on analysis of the hair mask obtained by an automatic segmentation. They use region growing process based on a color model of hair. Once the hair mask is segmented, they characterize hair style and define parameters (length, volume, color, symmetry, etc...). Their results are quite good unfortunately they are not robust enough when hair and background are not uniform. Moreover evaluation is done using a subjective criterion.

Our goal is to find hair in picture whatever form it arises and with different background conditions. The method we have to use should be adaptive to take into account the diversity of hair position and hue. Our algorithm is divided into two steps. Firstly, we perform a raw segmentation based on frequential and color analysis to place markers in hair regions. Secondly a matting process is achieved to get the final hair mask. Experimental results are evaluated using semi-manual segmentation references.

This paper is organized as follows. Section 2 presents matting process. In section 3, we present our algorithm of hair segmentation. Section 4 shows our results and we conclude in section 5.

2. MATTING PROCESS

The principle of matting process is the creation of a composite picture by adding some foreground features on a background scene or by changing the background scene. Matting method takes as input an image considered to be a composite of a foreground image *F* and a background image *B*. The value of the i-th pixel is assumed to be a linear combination of the corresponding foreground and background values:
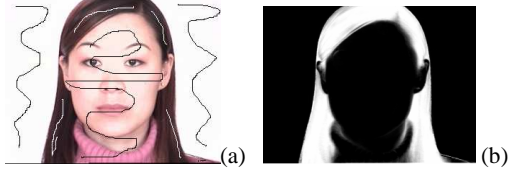
Fig 2. "*Matting process*" Example of alpha matte estimated (b) by matting process initialized by markers manually drawn (a). White curves represent foreground markers and black curves represent background markers.

$$C_i = \alpha_i F_i + (1 - \alpha_i) B_i \qquad (2.1)$$

where α is the pixel opacity or the blending component introduced in 1984 by Porter and Duff [3] .

Matting process consists in evaluating the alpha plan called 'alpha matte' in order to estimate the foreground and background plan. In our case, we need only the estimation of the alpha matte to segment hair.

Most of the recent methods use a trimap based on the Ruzon and Tomasi work [4]. A trimap is a rough segmentation of the picture in three regions: the known foreground coded with alpha equal to 1, the known background coded with alpha equal to 0 and the unknown region where alpha must be estimate. In KnockOut algorithm [5], F and B are assumed to be smooth and the estimation is based on a weighted average of known foreground and background pixels. In Bayesian matting algorithm [6] the local distribution is modelised thanks to a set of oriented Gaussian. F, B and alpha are estimated to be more suitable with the Gaussian distribution. In Poisson matting [7], the alpha matte is computed from a continuous matte gradient field by solving Poisson equation using boundary information from the trimap.

The creation of a trimap is not adapted to our automatic approach of hair segmentation. Trimap-based approaches give good results when unknown regions are narrowest as possible and if F and B are well defined. The method developed by Levin *et al* [8] [9] is more suitable for our problematic of an automatic segmentation. Making assumptions on local smoothness of foreground and background values, they show that foreground and background values can be analytically removed and they define a quadratic cost function only depending on alpha. They estimate the alpha matte by solving a sparse linear system of equations. Finally, they achieve to obtain precise alpha mattes on natural image from only a small numbers of pixels which replaced the trimap *(Fig 2)*. We call these pixels 'markers'.

3. HAIR SEGMENTATION

In this section, we present an algorithm for automatic detection and segmentation of hair (Fig 3). Our approach consists in the best automatic definition of markers placements in order to obtain a good alpha estimation by matting process. We define markers positions from information obtained by frequential and color analysis.

3.1. Definition of the "Head area"

Even if hair position is highly variable, we can consider that hair is around the face. We have to define a "Head area", which
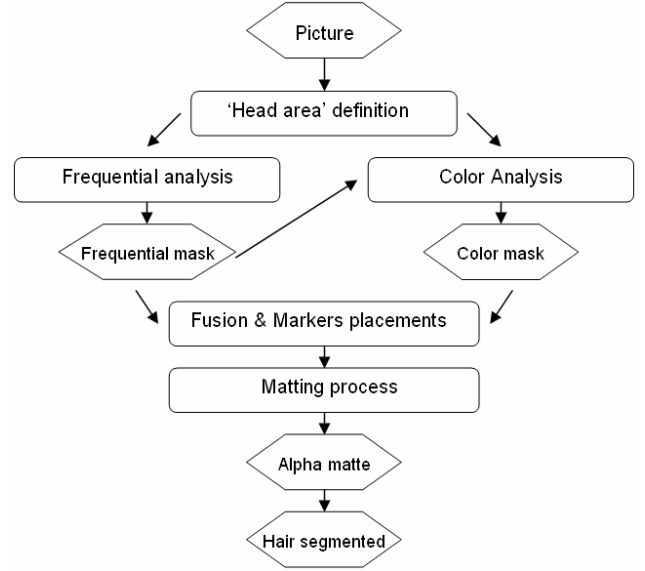

Fig 3. "*Hair segmentation algorithm*" Representation of the sequence of hair segmentation process

represents where the hair has the most probability to be present taking into consideration most of the hair type. We employed Viola and Jones algorithm [10]. The algorithm detects the face of each person in a picture and defines boxes including each face. The defined box is centred on the face and is not taking into account the hair. We define a "Head area" in order to include the hair into a new box *(Fig 4.b)*. This box is calculated from the size of the Viola and Jones' box and anthropological data generally used for face drawing:

$$\text{'Head area' height} = 2 * \text{Viola height}$$
$$\text{'Head area' width} = \frac{5}{3} * \text{Viola width} \qquad (3.1)$$

3.2. Frequential analysis

As hair has a particular texture aspect, we search to characterize hair with a frequential analysis of the picture. We define the isotrope Gaussian bandwidth filter :

$$hair\_filter(f_0, \sigma) = \int_{\theta=0}^{360} e^{\frac{-(f_\theta - f_0)^2}{2\sigma^2}} \qquad (3.2)$$

with f_0 the central frequency and σ the bandwidth.

Applying this filter gives a frequential map. Then we threshold this map using equation:

$$frequential\_mask(i, j) = \begin{cases} 1 \text{ if } frequential\_map(i, j) <= \mu\text{-}\sigma \\ 0 \text{ else} \end{cases}$$

(3.3)

with μ the mean and σ the standard deviation of the frequential map. Then we use morphomath treatment and labelling approach to remove artefacts or small objects.

The threshold area includes hair and unfortunately some other features of the image:
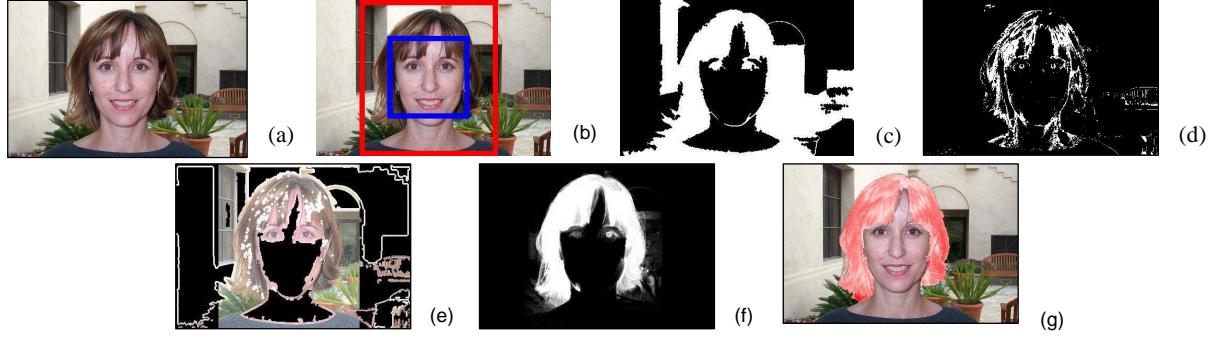
Fig 4. Description of the steps of the hair segmentation algorithm: (a) Initial picture, (b) 'Head area' definition, (c) Frequential mask, (d) Color mask, (e) Fusion & markers placement (white markers represent foreground and black markers represent background), (f) Alpha matte estimated, (g) Hair segmention

- Some parts of the background could be confused with hair. (Clothes, textured walls and objects, trees ….)
- The facial internal features can be detected too.

Frequential mask is not relevant enough to achieve good hair segmentation. We need to add more information. This will be done using color .

3.3. Color analysis

Hair color is one of the common parameter that people tell about to describe someone. Color appears as a good descriptor to find hair localization. According to the difficulty to define a precise and unique color for hair, we assume that creating a color model is insufficient to describe the entire hair mask. This model can be suitable for markers placement.

The color analysis is divided into two steps: first, we calculate a color model of hair based on image analysis. For time being we work only with hairy people. We define a sample window at the top of the face where to compute the color model. We use color information present in the area defined by the frequential mask. We suppose that hair is only present on frequential area.

Secondly, for each color plan in the YCbCr color space, we calculate the average color (μ_r, μ_v, μ_b) and the the standard deviation $(\gamma_r, \gamma_v, \gamma_b)$ of the sample window.

We create a binary color mask (*Fig4.d*) following the equation:

$$color\_mask(i,j) = \begin{cases} 1 \text{ if } \begin{cases} I_{(r,g,b)}(i,j) \geq \mu_{(r,g,b)} - \gamma_{(r,g,b)} \\ I_{(r,g,b)}(i,j) \leq \mu_{(r,g,b)} + \gamma_{(r,g,b)} \end{cases} \\ 0 \text{ else} \end{cases}$$

(3.4)

3.4. Fusion and Markers placement

Once we have created the two different masks (frequential and color), we need to keep only the common information from both masks. We intersect the information taken from the frequential and color mask using the logical AND operator:

$$\text{Fusion mask} = \text{Frequential mask} \bigcap \text{Color mask} \qquad (3.5)$$

We have now created a new binary mask which represents the most probable hair position. Before starting the matting treatment,

we have to place the white and black markers (*Fig 4.e*). We place white markers (foreground) inside the fusion mask. The black markers (background) are placed outside the frequential mask and inside the frequential mask out of the 'Head area'. Finally, we perform the matting process according to the section 2. The hair segmentation is demonstrated applying the alpha matte (*Fig 4.fg*) to the initial picture (*Fig 4.g*).

4. EXPERIMENTAL RESULTS

4.1. Image database

We work only on database with women faces in frontal views. We can explain our choice with following reasons: Firstly working only with face view limits the possible cases and we could use facial detection as starting point of our process. Secondly we use only women models because women have more different hairstyle which includes a part of men hair style and we avoid facial hair problem (beard, goatee, and mustache).

4.1.1. Home database (1)
This data set is a collection of 300 images (768 x 576 pixels) of different faces. Each picture was taken using a uniform background under fixed lighting conditions. This database is interesting for the hair diversity

4.1.2. CALTECH database (2)
This data set is a collection of 450 images (896 x 592 pixels) of 27 persons. Each picture was taken under several lighting conditions and background. We have intentionally selected this database to test our algorithm in case of variable backgrounds. (Images collected by Markus Weber in 1999 for California institute of Technology)

4.1.3. Hair mask reference database (3)
Hair mask reference doesn't exist. We have to create one in order to compare our results. Creating manually a pixel by pixel data base would be tedious and time consuming, so we decided to avoid it. Moreover precision of manual segmentation depends of the operator's judgement.

We prefer to generate our baseline by mixing manual information and automatic process. We create the database with a matting treatment from an image marked manually. In one hand, by marking manually the picture, we can mark correctly each area

corresponding to hair. On the other hand, with the matting treatment, we take into account the small artefacts of the background near the hair that we cannot take off with the automatic hair segmentation.

4.2. Performance measurement

We measure the performance of our algorithm based on 2 criteria. We calculate the false rejection rate (FRR) and the false acceptance rate (FAR).

- The *false rejection rate* is the measure of the likelihood that the biometric security system will incorrectly reject an access attempt by an authorized user. In our case, *FRR correspond at percentage of pixels who are in the mask hair obtains by manual mark and aren't into the hair mask obtain by automatic mark*

- The *false acceptance rate* is the measure of the likelihood that the system will incorrectly accept an access attempt by an unauthorized user. In our case, *FAR correspond at percentage of pixels who are in the mask hair obtains by automatic mark and aren't into the hair mask obtain by manual mark*

4.3. Result evaluation

	Rate of false refusal	*Rate of false acceptance*
Base (1)	9 %	14,2 %
Base (2)	4,8 %	38,7 %

Tab 1: Results obtained for a set of 200 pictures (1) and 155 pictures (2)

Results (1) show hair segmentation with an average rate of false refusal of 9 % and an average rate of false acceptance scoring at 14.2%. After segmentation, 90 % of the images have an average rate of false refusal less than 20 % while more than 75 % of images have an average rate of false acceptance less than 20 %.

Results (2) show to us hair segmentation with an average rate of false refusal of 4.8 % and an average rate of false acceptance is of 38.7%. After segmentation, 95 % of the images have an average rate of false refusal less than 10 % while only 55 % of images have an average rate of false acceptance less than 20 %.

We can generally illustrate the false refusal when roots or highlight lock are missed. On the contrary, the false acceptance can generally be illustrated when locks are in front of facial features, some clothes or background elements are similar to hair.

5. CONCLUSION

We achieve, in the majority of the cases, to segment the entire hair mask. Our development has been focused to be adaptative on different hair styles and background conditions. The combined use of two masks obtained by frequential and color analysis leads to a raw hair localisation in the picture. It's a good first approach to provide relevant information to place markers. The choice of matting approach represents a good way to segment hair mask especially because it can be very adaptive to the model defined by the markers. We achieve to segment as well long hair *(Fig 5.c)* as split hair region like ponytail *(Fig 5.d).*

We perform our algorithm using Matlab solver on a 3 GHZ CPU. Computing time is about 20 seconds using unoptimized Matlab code for image of 200 by 300 pixels.
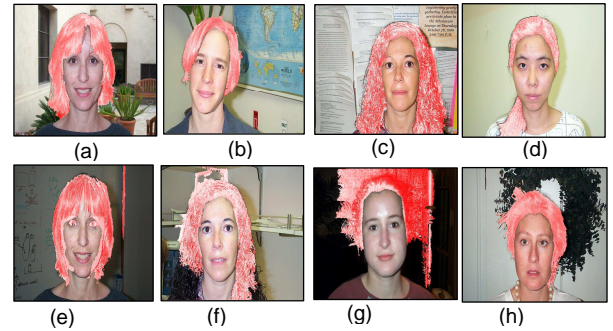

Fig 5: Examples of hair segmentation

Our algorithm is still limited in the following aspects:

- The frequential and/or color information are not perfect, and we can marked some non hair pixels *(Fig 5.e, 5.f)*. We should search others parameters for characterize hair localization and introduce a weighting function for the definition of the markers based on the distance to the face. Even if we couldn't define exactly the hair position, we can assume that hair is around face.
- The markers are well placed on hair but their localization and the lack of color information *(Fig 5.g)* lead to bad estimation of the alpha matte.
- Our detection had natural limits and even a human operator could hardly achieve good hair segmentation. Some background features are very similar to hair in frequency and in color *(Fig 5.h)*

As a future work, we may introduce hairstyle model to guide the segmentation process.

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