# REDUCING FALSE POSITIVES BY MARKING AND OVERCLASSIFYING

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*In this paper we propose a metaheuristic to increase the selectivity of a classification method, i.e. the reduction of the false positives (FP). The main idea of our contribution is to give a partition - the partition is not exact, but fuzzy - for each class provided by the initial classification method, finding additional conditions to refine the classification inside each class. In order to assure the correctness for these conditions and to assure the reduction of the FP we use perceptual information, i.e. classification marks provided by human expert [Georgescu 1, 2012] If we name prototypes the classes obtained inside each initial class by partitioning, the selection scheme is: interest_regions = prototypes_regions ∩ marked_regions.*

**Keywords:** classification in images, metaheuristic, fuzzy, human expert, skin detection, reducing false positives, fault tolerant

## 1. The experimental framework

Our procedure for reducing FP could be generalized for other classification problems, even if we treat the specific problem of the Skin Detection (SD). SD corresponds to the fact that we start with a classification method with two classes: skin and non-skin. Let us remind that selecting skin is of great concern as a previous step - if it is not a final problem - before accomplishing other tasks that operate "inside" skin regions, e.g., red eyes reduction, face detection or facial features analysis. As

The additional conditions to refine the initial classification refer the skin class – the non-skin class is out of our interest: we assume that, for our SD method, the FP are negligible. In general, the major problem with SD methods is that they detect too much FP, i.e. they select regions that actually do not correspond with skin as skin regions. Conform [1], "recently, skin detection methodologies based on skin-color information as a cue has gained much attention as skin-color provides computationally effective yet, robust information against rotations, scaling and partial occlusions." In [2] we presented other advantages of these pixel-based methods. In [2] we also talked about the

importance of choosing of a color space with a good decorrelation between chrominance and luminance and we design such a method with good results.



| F: a photo with 'flash' | 'Skin Detection' for F ( black color) |

Fig. 1. Typical Skin Detection method: there are many colors with a skin-like chromaticity; for the luminance, we apply two global threshold → the far skin regions are not selected due to the inferior threshold.

The inferior threshold has an explanation in our concrete project: we are interested to select near faces, as we intend to perform a red eye reduction inside these regions. We could see the big influence of the flash direction. It is only one of the possible big influences – we could also meet shadows and specularities.

The additional conditions to refine the initial classification come from a comparison between the photo with 'flash' (F) and the photo without 'flash' (P, from preview: we have access to the preview just "before" F). F and P are two different images, obtained in significantly different conditions - while F has important corrections (e.g., white balance, P has not). We could not compare these images as chromaticity. It seems that the only comparison that could be done is regarding the luminance component → we use Dif = F – P on luminance.

### 2. Skin / non-Skin classification. Skin subclasses

Our idea is to define the Skin Locus (SL) in a Perceptually Uniform Color Space, in order to partition SL (the skin class) in disks (subclasses) with the same area. We chose the Lab color space for its benefits:

- It provide maybe the best decorrelation between chrominance and luminance

- Maybe the broadest color space for researching, next we could approximate the conclusions in another color space

- Color is a human perception – JND (Just Noticeable Difference) is a good measure of this fact in Lab space [3]. Besides, the partitions could overlap each other in a certain degree – inside the SL, we could further establish degrees of membership to each disk / prototype $D_i$ for a pixel: we talk about fuzzy partitions and that open a gate to the soft computing
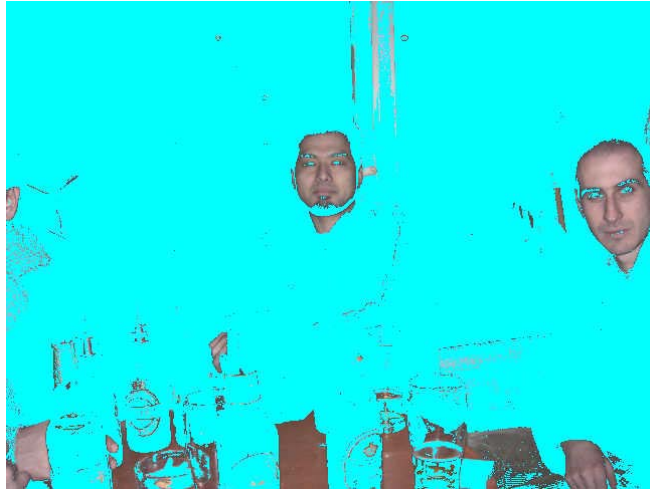
We design and implement a SD method:



Fig. 2. Our Skin Detection method has a a good rate of false negatives and also positives, for a large category of people

We compared the performance of our SD method with other appreciated SD methods: the method Hsu defined in [4] – it has the remarkable property that in YCbCr color space, the SL is a compact ellipse – and a method defined by inequalities [5] – the great advantages of this method are the speed and the minimum requirements of memory, as we mention in [2]. We compare these methods in different chromaticity planes and with reference to the skin color chart of Felix von Luschan".
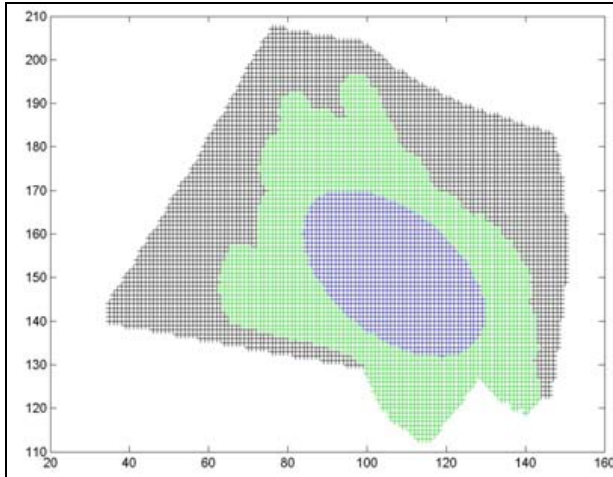
Fig. 3. Skin gamuts in CrCb chromaticity plane (from YCrCb color space), conform with the three methods: blue – conform with [4] method (Hsu), green – conform with our method, black – conform with [5] method (Berbar)
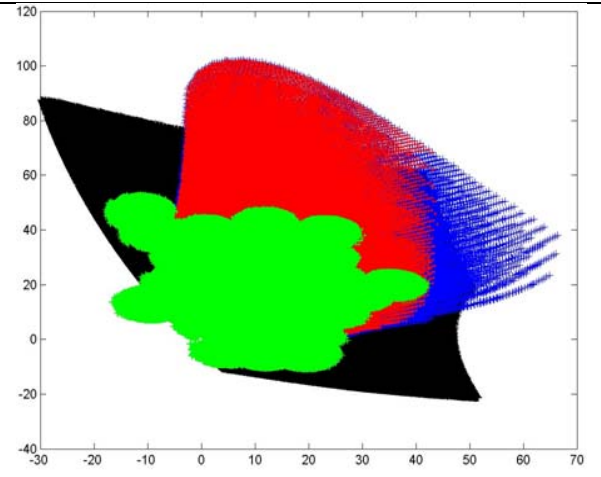


Fig. 4. The same Skin Locus in CrCb chromaticity plane (from Lab color space) – red denotes an inferior global threshold for the luminance component conform [4]. We observe that our representation, with disks, is the compactest.
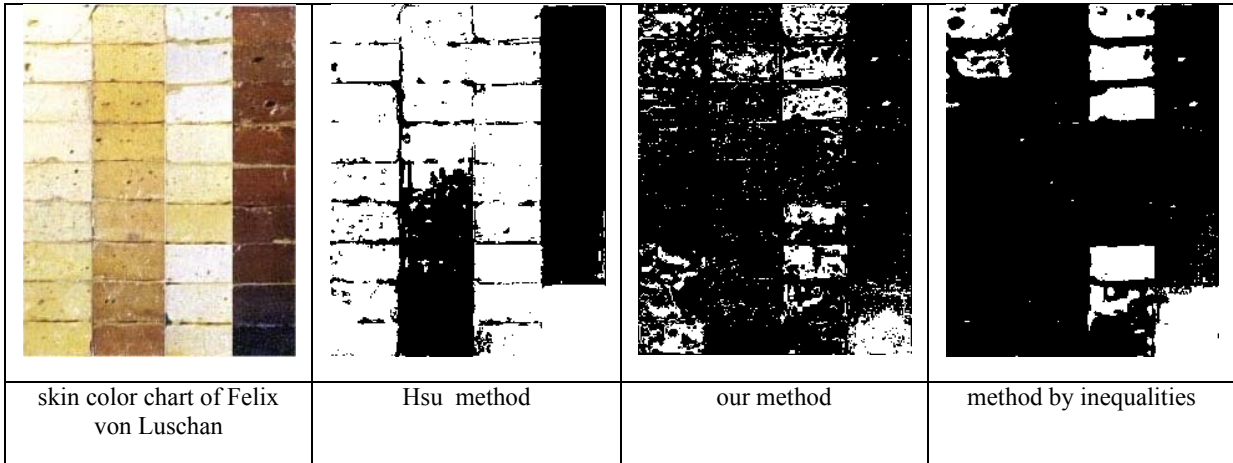


| skin color chart of Felix von Luschan | Hsu method | our method | method by inequalities |

Fig. 5. Comparison with reference to "the skin color chart of Felix von Luschan". It is confirmed that our method has the best coverage – we could neglect the false negatives problem

## 3. An algorithm based on the luminance change for each skin prototype

Conform to the above introductions, we present an original Skin Detection method. It consists in three stages:

Stage I. Detecting skin prototypes regions in the image obtained with flash (F):

$$\boxed{F} \implies \boxed{\text{DetectSkin tool}} \implies Z1 = U R_i, \ i = 1 \ \text{to} \ n \quad (1)$$

, where Ri correspond to the skin prototype Pi. Each pixel in Z1 is labeled with the correspondent skin prototype.

Stage II. Computing Dif = luminance (flash – preview), after noise reduction in P and registration (alignment and resizing) F with P. Shortly written:

$$Dif = F - P \qquad\qquad (2)$$

$$(P, F) \implies \boxed{\text{LuminancesDif tool}} \implies Dif$$

Stage III. Determining the thresholds for each skin prototype (Pi) – pseudocode for the training algorithm:

In order to determine the thresholds (inferior and superior) we will process a large (covering) amount of situations ((P, F) pairs) like this:

1) Initialization:

*for_each skin prototype (Pi)
        Initialize the inferior threshold (t) and the superior (T) at the
        maximum, respective minimum value possible

2) The effective training algorithm:

*for_each <situation (P, F)>

        - inside Z1 mark (the software use Z1 as a mask to implement this
        "inside") manually the real skin regions $\implies$ interestRegions   (3)

* for_each interestRegion
      for_each <pixel ∈ interestRegion>  modify the thresholds like this:

- let $P_i$ be the prototype label set at the first stage în cadrul etapei  I
     and let    L be the luminance of the pixel in Dif.
    // $Pi.t$ şi $Pi.T$ behave like "prototypes' thresholds"
     - if ( $L < Pi.t$ ) => $Pi.t = L$
      - if ( $L > Pi.T$ ) => $Pi.T = L$;

At the end of this algorithm, we will have for each skin prototype (Pi) the inferior threshold ($Pi.t$) and the superior one ($Pi.T$). Concluding, the method sketched will select the pixels the properties:

*Criteria: cromaticity(pixel) belong to a skin prototype Pi   AND*
$$Dif (pixel) \ belong \ to \ [Pi.t, \ Pi.T] \qquad (4)$$

*Observation: The marking (3) does not have to be exact to improve the selectiveness of our method*: the reduction of false positives is fault tolerant using the mask Z1 determined at stage I. Of course, the better the marks, the better the reduction of FPs.

## 4. Noise reduction and image registration in our concrete case

The image obtained without flash, i.e. the preview P, has a poor quality – besides the fact that it is taken in poor conditions (darkness), it does not benefit by the corrections that come for the image obtained with flash (F), e.g. white balancing. We aim to make P comparable with F, on luminance, in order to compute (2).

We tested on hundreds of situations, with very different parameters: orientation, distance, illumination, indoor/outdoor etc. The noise appear to be uniform rather than not. However, without manifests a clear regularity. 'Hot pixels', i.e. pixels with luminance in excess, appear frequently in P. The noise reduction consist of: resizing P to a common size with F (the greatest common divisor) and applying a rank filter: from a sequence of four values, we choose the second – we observed that the image extracted this way is the smoothest.

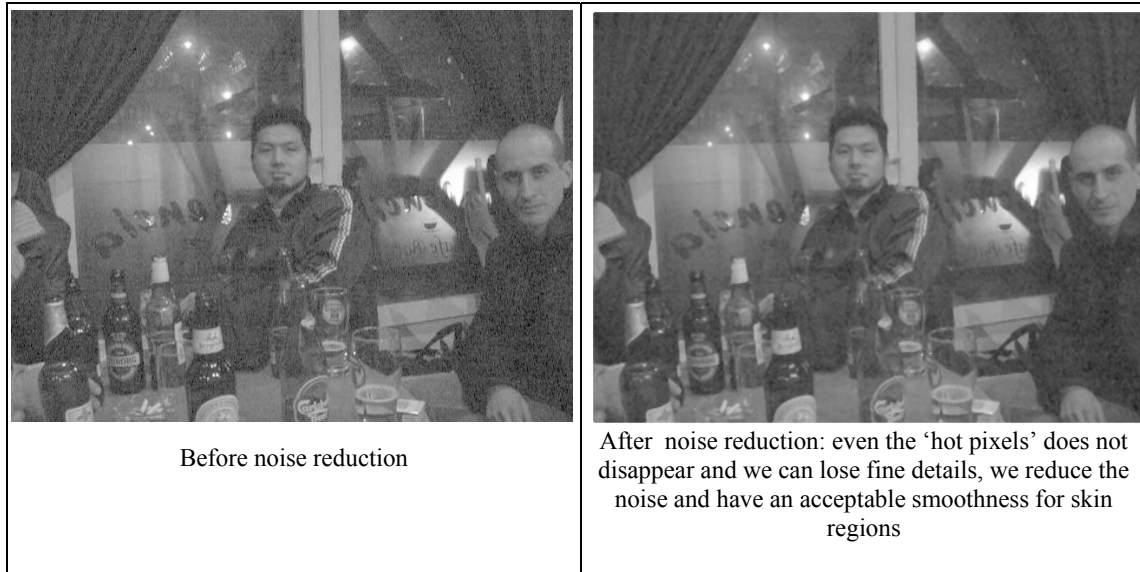| | |
|---|---|
| Before noise reduction | After noise reduction: even the 'hot pixels' does not disappear and we can lose fine details, we reduce the noise and have an acceptable smoothness for skin regions |

Fig. 5. Noise reduction

We could also eliminate other artefacts of shadows and specularity using the 'bilateral filter' designed to produce a 'large scale' version of the image averaging the closed pixels as distance and luminance conform [6] and [7], using the gradient techniques [8] or estimating the reflectance [9]. But these methods are too expensive for a firmware (we intend to implement a Red Eyes Reduction algorithm 'in camera') and, especially, they do not offer an acceptable support for calibration. We also tried to apply a factorial model for the exposure time: $E = k\ g\ T\ ISO$, where k is a constant dependent on camera, g is the CCD gain, T is the exposure time and ISO is the camera sensitivity. This formula proved also to be unrealistic. A useful approach to cope with dark previews and artefacts of shadows was the *pre-flash*, which by design decreases the rate of 'red eyes' – some digital cameras fire a pre-flash just micro-seconds before the main flash and that makes the subject's irises contract; in plus the image obtained with preflash is more comparable with the image obtained with (full) flash.

The registration P with F was implemented using a 'phase correlation technique'. A major problem when computing Dif is the movement between P and F.
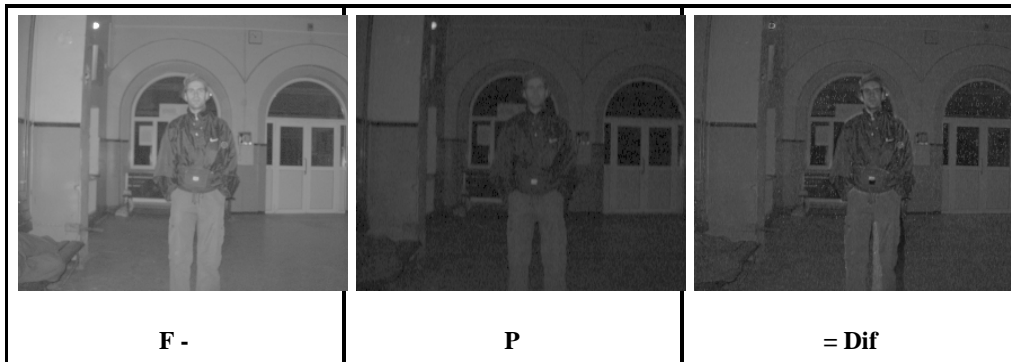
| F - | P | = Dif |

Fig. 6. The movement of the photographed person between P and F could affect the relevance of Dif introducing some suplimentary neregularities.

We assume that we could detect and skip these situations. We could also use statistic techniques, voting techniques to adapt the algorithm presented alt chapter 3. Anyway, it seem that is hard to compare P (with preflash or not) relative to F, the comparison on luminance being the single variant. We tried to use a ratio or adaptive difference instead a simple difference. We keep the simple difference. Moreover, even skipping the neregularities, the relevance of Dif depends on the environment, flash direction and so on.



| Fig. 7. $\Delta I$ , i.e. the difference   on luminance, relative low, for outdoor environment, the flash direction being not on the face | Fig. 8. $\Delta I$  relative high for indoor environment, the flash direction  being on the faces |

## 5. Discussion after experiments

Let us analyze the robustness of our method taking some key situations.

Fig. 9. Dif for a situation when some light comes from lateral (the left side of the characters) → blacked regions with skin: if we take in account these regions in the stage III of the algorithm, we will enlarge the luminance interval corresponding to some skin prototypes, decreasing the inferior threshold Pi.t.

However, even we do not skip some neregularities, by design, the selectiveness of the method will increase – example:



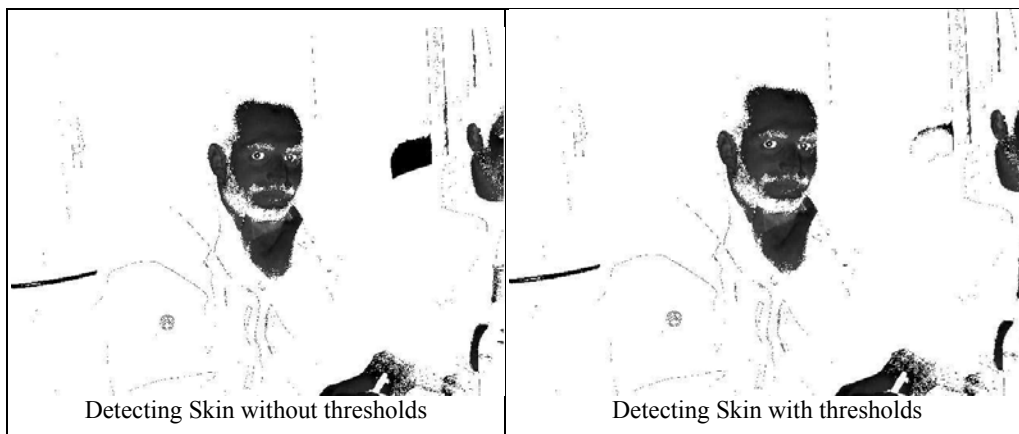Detecting Skin without thresholds                   Detecting Skin with thresholds

Fig. 10. A situation when applying the thresholds reduces the false positives – observe the removal of the region between the two faces

In the photo obtained with flash we observe that the region mentioned above  could be easily detect as a skin region:

Fig. 11. The region mentioned in Fig. 10, in the photo obtained with flash

### 6. Conclusions and further work

In this paper we propose a 'pixel based' metaheuristic to reduce the false positives (FP) for a selection method, using marking (by the human expert) and overclassifying (inside the input classes). The main idea of our contribution is to give a (fuzzy) partition for each class provided by the initial classification method. If we name prototypes the classes obtained inside each initial class by partitioning, the selection scheme is:

$$\text{interest\_regions} = \text{prototypes\_regions} \cap \text{marked\_regions} \qquad (5)$$

The overclassifying corresponds to Skin Locus partitioning. We could do this in the Lab color space - taking in account perceptual uniformity of this space, we break the SL chromaticity in disks (prototypes). These disks could overlay each other – it is a fuzzy partition. The relation (5) is refined to:

$$\text{cromaticity(pixel)} \in \text{Pi prototype} \quad \text{AND} \quad \text{Dif (pixel)} \in [\text{Pi.t, Pi.T}] \qquad (6)$$

whwrw the thresholds Pi.t şi Pi.T are computed by the training algorithm exposed at the chapter 4. To optimize the performance of the detection the training run on images as much closest as possible to the images for we apply the selection / detecion method. This is an adaptive training. Porting the SD method to another category of images will consist only to run again this preprocessing step.

Another important advantage of our metaheuristicis that, practically, it is a very useful tool for research. Thus, we could demonstrate, the utopy of some classification problems – like the separation theorem in [10] talked about a "maximum degree of separability" between two convex fuzzy sets (we could see the prototypes Pi as fuzzy sets).

Further work could be done in the following directions:

- increasing the granularity of the prototypes;

- increasing the "naturality" / separability of the prototypes – eventually "clusterizing";

- by morphological processing we could remove the neregularities;

- designing the prototypes as fuzzy sets – although the partitioning method is fuzzy-like (the partitions could overlap each other), we do not designed the prototypes as fuzzy sets. This could bring a better control for the prototypes, flexibility ant interoperability withother fuzzy entities, therefore to a powerful clasification method.

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