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Eye Color Classification for Makeup Improvement

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Abstract—**The development of computer-aided solutions able to suggest the right facial makeup is a recent trend in image analysis applications, from which both amateurs and professionals could benefit significantly. The global harmony of a person is highly valuable when choosing makeup colors to make a person looking lovely. The global harmony is evaluated taking into account the color of the hair, skin and eyes, and among these features, the eyes seem to be one of the most salient features that capture an individual attention. This paper proposes a simple yet effective eye color classification scheme, compliant to the categories associated to the cosmetic software, which are often different than the classification systems used in medicine or biometrics. The color descriptors are histograms of the iris color distribution in the HSV color space, classified by multi-class Support Vector Machines, and the high accuracies achieved recommend it for digital cosmetic assistant solutions.**

I. INTRODUCTION

ALTHOUGH the eye (iris) color and appearance is important for various classes of applications, most reported works concern the analysis of the iris for medical and biometric purposes [1]-[6], and less effort was so far devoted to the needs of the cosmetics industry. This issue is addressed in this paper. In the latter case, particular classes of eye colors are defined, and often subjective assessments and most of the times not well defined mathematically criteria of describing the eye color are applied. Therefore extracting the best features from the iris image deciding their class assignments is a non-trivial task. Overall it is reasonable to say that the facial image analysis in general devoted to the design and development of computer-based facial makeup assistants is a new direction in the scientific community, focused on learning-based approaches, which seem the most reasonable choice, as long as we take into account that the best makeup for an individual is rather an "art" than a well-defined problem, which should consider the social context, the ethnicity and the overall characteristics of the individual [7]. In fact, the most recent solutions for computer assisted face cosmetics are based not even on linguistic or rough descriptions of the face features and explicit associations of these descriptions with a specific type of makeup, but rather on sets of example digital face images without makeup and with professional makeup, on which a software system is trained to infer correspondences and transforms of a new face without makeup, to yield the closest result to the example from a professional. Some examples of such systems can be found in [8], [9].

A different type of approaching the computer-assisted makeup would be based on an independent classification of the important face features. When talking about face features we refer to skin tone, color of eyes and hair; all these elements give the "global harmony" of a person. There is a whole theory in the makeup area which involves blending colors in, matching them to eyes and skin tone and hiding facial irregularities. The color is most often considered to be a dominant feature in cosmetic makeup decisions, to suggest the makeup colors properly for each individual. There are some US patented inventions [10]-[12], not in the form of software products, but makeup "kits", to determine the eye-shape, skin-tone or personal matching makeup color; yet none of these products have emerged the cosmetic market so there is still place for research in this area. Just like in the case of "whole-face" computer makeup assistants, in the case of the systems working on each facial feature independently, the classification of the facial features based on their color and appearance may not be a simple task, as the classes themselves are defined by a makeup specialist, and the description of the salient features is generally hard to transpose directly in a mathematical form. The solution to the classification task can again (like in the image example-based approaches) the employment of a machine learning strategy, to associate a set of features to the makeup specialist defined classes.

In this paper, we focus on a particular type of facial feature, that is, the eyes color. The eyes were often considered in the cosmetics industry as one of the most important features of the face, therefore a lot of attention goes on their right make-up [6], which should match to the shape and color. Here we consider only the iris color classification problem, in a way compliant to the makeup professional criteria, with the aim of providing an accurate classification system, able to work on natural face images,

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acquired under various resolutions and environments. This system will be included in the future into a digital makeup assistant. To this end, several color features are examined, extracted from the most commonly mentioned color space in the cosmetics industry (that is, the Hue-Saturation-Value – HSV – color space), and their suitability is assessed by the means of a learning-based classifier: multi-class Support Vector Machine (SVM). Considering the subjective assessment of the eye color (specific to humans), we do not restrict to a simple set of color descriptors. Instead, taking advantage of the ability of SVMs to learn in high-dimensional feature spaces, even from few training samples, we examine several forms of normalized color histograms of the iris defined in the HSV color space as feature vectors. This approach is sometimes encountered in the literature for difficult to define classification problems, as e.g. ultrasound tissue classification using Fuzzy Local Binary Patterns histograms and SVM [13], or lip color classification [14]. One way of extracting the features of the eye into a vector was to simply concatenate the Hue (H), Saturation (S) and the Value (V) histograms with different granularities into one single vector. Another way to represent the features was equivalent to the form of multi-dimensional histograms. This form of histograms correlates more the appearance of each possible combination of H, S and V among the considered pixels.

In respect to the definition of eye colors categories, we consider two different sets of classes (specifically defined for compatibility with the makeup applications, in the view of our future intended work). The first one is suggested by a makeup artist, whereas the second represents an aggregation of the eye color classes defined for various types of applications in the scientific literature (from general purpose and genetics to biometrics and medical diagnosis: [1]-[6]) into a new color-scale system. The system suggested by the makeup artist was referring to an “eye harmony” given by the combination of two characteristics of colors: lightness and warmth. The proposed color grading comprises six colors, namely: Blue, Blue-Green, Brown-Green, Gray-Hazel, Brown and Dark Brown, which proven sufficient to describe the color palette found in the iris of a human eye.

The classification results on the PutFace database [15], under both color categories systems mentioned above, are very promising, exceeding 92% and going even up to 100% in some cases, which is slightly superior compared to similar results in the literature (devoted to eye color classification, although for different purposes than the one addressed here – for which we did not have a reference).

II. Eye color classification systems

The general appearance of the iris is an important clue for many facial image analysis tasks [1], [3], [4]. The iris comprises two layers, the anterior one is translucent and the posterior one is heavily pigmented. The amounts of melanin produced by the anterior layer together with the pigments of the posterior layer determine the actually perceived eye color through a combination of light absorbance, reflectance and scattering. Actually, the iris “color” is not uniform; there are different colors that compose the iris, but finally they are perceptually described by humans through a single label, according to the dominant sensation. Classification is not difficult only because the iris colors and textures change depending on how they are examined, but also because these colors form a continuous palette. Under these conditions, it is understandable why it is difficult to have a standardized eye color classification system.

A number of genetic studies have been performed in order to establish a chart or a scale for human eye color. Various classification systems have ranged from a basic “light” or “dark” description to detailed grading employing photographic standards for comparison.

For example, J.M. Seddon et al. established a five-grade classification system [2], based on the predominant iris color and the amount of brown or yellow pigment present. There are three true colors (not pigments) observed in the eyes that determine the outward appearance: brown, yellow, and blue. The appearance of the eye color is determined by the percent of each of these colors in the iris. Thus, green eyes contain yellow and some blue and sometimes brown, making the eyes appear green or green-brown. Gray eyes have a little yellow and a little or not at all blue and/or brown in them.

Another eye color scale, commonly used in physical anthropology since the beginning of the 20^{th} century, is the Martin-Schultz scale [1], comprising sixteen colors. The anthropologist Carleton Coon further classified these sixteen colors into a chart with only three main categories: light eyes, mixed eyes and dark eyes. For an even finer grading of the iris color, Franssen et al. [3] proposed a 24-scale system from least to most iris pigmentation, which is similar to Martin-Schultz scale. These grading systems are generally thought as references by visual observers, in the classification of iris images, by comparing the on-line image of an individuals’ iris to the standard Martin-Schultz glass-made eye-scale or to a set of reference iris images (painted or photographs). However these color grading standards are devoted rather to medical or biometric applications, and they find little applicability to cosmetics and makeup industry.

There are some very recent attempts to develop automatic eye color classification systems. Prior to describing them, we should also emphasize that most of them are devoted to biometrics and medical diagnosis, thus the goal of iris image analysis in such cases is clearly different than cosmetics. German et al. [17] presented the classification of the iris color and the iris response to a certain drug. The color was analyzed using RGB color space. In 2000, Melgosa et al. [18] performed the iris color quantification using CIE L*a*b* color model. In 2001 Takamoto et al. [5] developed an algorithm which can identify the iris color from several pictures of the same iris but taken at different exposures. Fan et al. [19], in 2003, proposed a method of both quantification and correction of the iris color using CIE L*u*v* color space. This method is useful because offers also a color correction method. In 2008 Franssen et al. [3] presented a new iris pigmentation classification system based on comparison of iris pigmentation to a set of 24 standard eye photographs (from least to most pigmented), with the aim of gaining on accuracy and on applicability for retinal straylight studies.

Studies regarding the classification of iris color have appeared more and more often in later years, as it can be seen from this short history; in this sense, several important researches in the automatic iris classification were presented in 2011. For instance, Dantcheva et al. [20] performed a research for automatic eye color recognition for biometric purposes. In that paper, the eye colors are classified in 4 classes with Gaussian Mixture Model in RGB space. They tested the algorithm with manual and automatic segmentation of the iris area. They have weaker results for blue and green colors; overall, for manual extraction of eye color the accuracy ranges from 81% for green to 100% for black and brown. When using an automatic segmentation of the iris, the classification accuracy decreases, ranging from 75% for blue to 91% for black.

Lodin proposed in his two papers in 2011 [21][22] an automatic iris classification, suitable for medical purposes, using the intra-palette color merging technique in CIE L*u*v* color space, the Gaussian Mixture Model and the Euclidian distance between similar colors.

From the significantly smaller number of approaches using eye color for cosmetics – facial makeup, we will briefly review some patents. A process for making up the eyes is proposed in [16]. Three different individual colors of the iris of the eyes (comprising the iris contour color and the iris sparkle colors) are extracted and used for selecting make-up products, but these colors are only roughly described, in the form of a mean color computed from the corresponding regions of the iris image. These colors are further used to suggest the makeup by a simple search in a database, which may or may not lead indeed to an accurate match. In [12] the personal colors for facial cosmetics are determined by referring to skin, eye and hair color and relative intensity. The kit comprises a scale card or other value determining a scale which is used to determine the relative lightness or darkness of features. Comparing these features of an individual to an overall value, the scale for make-up appliance is obtained. In [10], having a makeup color image, a method for classifying the makeup material for each face region is provided. A color image index indicating warm/cool and an index indicating light/heavy are formed as two coordinate axes and the colors are located there along. Finally, the make-up color image map is extracted.

Whereas related to some extent to some of the above described systems, our methodology differs mainly in terms of the features and classifier used.

III. MAKEUP AND EYE COLOR

One of the most profitable industries in the last decades, “beauty” industry has extensively used the aid of cosmetic products and, in the era of automation, the need of automated software that would help in choosing the right products has arisen. There are some software applications that help/guide, either the amateurs or the professional makeup artists, to apply makeup on a person’s face - they usually take the form of “painting” with different colors over a face image. Examples of this kind of software are: Photo Makeup Editor, Beauty Pilot, AMS Beauty Studio and other.

The importance of choosing the right makeup comes from the need of humanity for everything that is beautiful, because a good looking person “sells” and mostly because makeup is at the foundation of a billion dollars industry represented by television, films & music industry, advertising, PR (Public Relations) and business.

The eyes are the focal point of a face [6]; therefore, with eye-makeup one can create a series of illusions of new shapes and sizes. Eye shadow should always coordinate with the eyes, to a less extent to hair and skin tone and almost never to the clothes.

When one’s starting to learn about makeup, first things are related to color theory [6]. There are some elements pointed out and understanding them is important, as they come into play in makeup color trends: the three dimensions of color; color harmonies; color reflectiveness – matte, shiny, metallic, opaque, translucent, transparent.

A. The three dimensions of color

The three dimensions of color, usually used in the right decision for makeup colors [6], are in fact the 3 dimensions of the HSV colorspace. HSV is the colorspace that is the closest one to the human way of describing the color. The Hue characterizes the dominant wavelength of the color, the Saturation is a measure of the purity of the color (also named “color strength”), whereas the Value describes the brightness or luminance of a color, from dark to bright.

The colors applied on a face as makeup must be selected carefully. First of all, the colors mustn’t all have the same gray value, as this may lead to a bad look of the client. The three dimensions of color (Hue, Saturation and Value) must all be taken into account when suggest a right makeup.

B. Color harmonies

In color theory, color harmonies are an important aspect. These color harmonies represent a collection of colors, that are considered to be pleasant for the eye, are formed by different color connections, represented mostly on a color-wheel, very encountered in the field of art, called The Real Color Wheel.

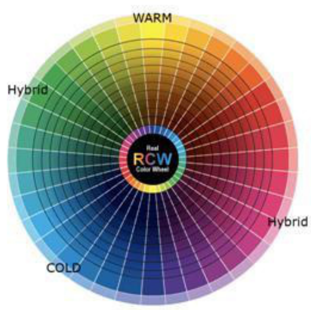

Fig. 1. The Real Color Wheel used in art

Even though the styles for makeup change from year to year, the global harmony of a face will always be taken into consideration [6, 23]. Accordingly, there are some common sense principles related to the global harmony, as follows. Warm, saturated, light value hues are "active" (active range is yellow-orange-red). Cool, low saturated, dark value hues are "passive" (passive range is green-blue-purple). Tints or hues with a low saturation appear lighter than highly saturated colors. Some colors remain visually neutral or indifferent (blacks). Extreme unity leads to under-stimulation, extreme complexity leads to over-stimulation.

'Color Harmony of a face' evaluation process implies tree steps: (1) Break the face into three main areas/feature: Hair, Eyes, Skin; (2) Classify each area/feature; (3) Evaluate the global Harmony from the classified local Harmony.

In this paper we address the problem of obtaining the Eye Harmony of a person. Each eye is extracted and categorized by a couple of labels obtained by grouping: Warm/ Hybrid/ Cold and Light/ Medium/ Dark, giving 9 classes of 'Eye Harmony'. For example: (Cold,Dark) or (Warm,Light). The classes for each area are defined using the Hue/ Saturation/ Value color model.

IV. The Classification Step Using a Support Vector Machine Classifier

A. Color histogram features for eye color description

A good selection of the feature space is well known to be crucial for the success of any classification scheme, as an ill-chosen set of features (carrying irrelevant information or simply not enough information on the problem to be solved) will make the classifier task very difficult or impossible without error. However, as previously emphasized in this paper, for the specific application aimed here, it is not so straightforward to define exact classification rules and exact features used by a human observer in assigning labels to the iris colors, according to the eye makeup rules. The general considerations in the makeup industry [6, 7] give us clue on the selection of the appropriate color space for describing the eye color, which leads to the selection of the HSV color space. The most salient features extracted from this color space being harder to define, a straightforward choice is to simply retain different forms of color histograms in the HSV color space, and examine the discrimination performance of a supervised classifier in each color histogram based feature space – as explained in the Experimental Results section.

Prior to extracting the color histograms from the iris region, the exact region of interest must be defined. Considering color face images of the individuals are available, the region of interest localization can be performed automatically or manually. There are standard automatic procedures for iris extraction, mostly consisting in a pre-localization of a rectangular image window containing the eye, after which the circular Hough transform may be applied on this window to extract the iris only. Since the iris localization was not the goal of our work, we chose to extract the iris area manually, transform the pixels in the iris area into the HSV color space and segment this area by a saturation thresholding in order to keep only the color region and exclude the pupil zone and the white reflections. The threshold was empirically set to 0.2 on a saturation (S) range of [0; 1]. The result of this pre-processing yields the set of iris color pixels, on which different forms of color histograms in the HSV space are computed and used as feature vectors, as follows.

One way of extracting the eye color feature vector was to simply concatenate the normalized linear histograms of the Hue (H), Saturation (S) and Value (V) components, computed independently on the above described pixels set. To maintain a reasonable length of the feature vector and to disregard irrelevant small variations within the representation of the same color, a uniform quantization (uniform Parzen window) of each variable range (on the same number of bins for each) was applied prior to computing the histogram. We denote the number of bins per color component by n_{Bins}, and the independent normalized linear histograms of the three color components (further called 1D histograms, as they are only computed over the one-dimensional "space" of a color component) by the vectors $\mathbf{h}_H[n_{Bins}\times 1]$ for the Hue, $\mathbf{h}_S[n_{Bins}\times 1]$ for the Saturation and $\mathbf{h}_V[n_{Bins}\times 1]$ for the Value. Then the color feature vector described as the concatenation of the three histograms will be given as: $\mathbf{x}_{1D}[3n_{Bins}\times 1]=[\mathbf{h}_H^T\ \mathbf{h}_S^T\ \mathbf{h}_V^T]^T$, in column form. We also consider and investigate color feature spaces obtained by a sub-set of the three 1D color histograms, e.g. using only the Hue and Saturation components, in which case only those normalized histograms will be concatenated in the resulting color feature vector, whose length will be, in the general case, $N\cdot n_{Bins}$, where N denotes the number of color components used (N=1, 2 or 3).

Another type of color features is formed by the normalized linear multi-dimensional color histograms, describing the number of co-occurrences of H, S and V values in the iris color pixels set, normalized to the number of pixels in the set. This form of histograms preserves the correlations of Hue, Saturation and Value in the description of colors. Denoting again by N the number of color components used for the generation of the multi-dimensional color histograms, N=2 and N=3 considered, we call the resulting feature vector, a normalized N-D histogram, which can be defined over the following input spaces: (H,S,V) – for the case N=3, and (H,S), (H,V), (S,V) – for the case N=2. In each case, the range of each color component is again quantized on n_{Bins} intervals, leading to a total length of n_{Bins}^N for the color feature vector, $\mathbf{x}_{ND}[n_{Bins}^N\times 1]$.

B. Multi-class SVM color histograms classification

For the process of eye color classification, Support Vector Machine classifiers (SVMs) were used, as they are powerful machine learning algorithms able to learn with good generalization and high accuracy from relatively sparse sets of training data. As many researchers conclude [24]-[26], SVMs are very suitable for face and voice recognition, biometrics and machine vision applications in general.

Implicitly, SVMs are binary classifiers, based on the optimal separating hyperplane [27], which is derived in the training phase based on training data to maximize the margin, and is used in the classification phase to assign class labels to new test data. For multi-class classification tasks, several generalizations of SVM classifiers have been suggested, among which the most simple are the "one-against-many" (or "one-against-all") strategies and the "one-against-one" strategy, where Q(Q-1)/2 binary SVM classifiers are built, and Q being the number of categories assigned to the classification problem. Mathematically, such a multi-class extension of the binary SVMs involves the definition of a set of binary discriminant functions: $f_y: \mathcal{X} \subseteq R^n \rightarrow R$, where $\mathcal{X}$ is the feature space, n is the dimension of the feature space, $y \in \mathcal{Y} = \{1, 2, \ldots, Q\}$ are the class labels, and each f_y is either the real-valued decision function (or, for more accurate results, a probabilistic mapping of the real-valued decision function) of an individual SVM classifier, defined in a general form as:

$$f_y(\mathbf{x}) = (\boldsymbol{\alpha}_y \cdot \mathbf{k}_y(\mathbf{x})) + b_y, \quad y \in \mathcal{Y}, \tag{1}$$

where: $\boldsymbol{\alpha}_y$ is the vector of the associated Lagrange multipliers multiplied by the training data labels (+1 or -1) of the training data for the current classifier y; b_y is the bias of the current SVM classifier, for the class y; $\mathbf{k}_y(\mathbf{x})$ denotes the vector of kernel functions evaluations, $K_y(\mathbf{x}, \mathbf{x}_i)$, for each training sample $\mathbf{x}_i$ associated to the SVM training for the class y.

The multi-class classification rule $g: \mathcal{X} \rightarrow \mathcal{Y} = \{1, 2, \ldots, Q\}$ is defined as:

$$g(\mathbf{x}) = \operatorname{argmax} f_y(\mathbf{x}), \; f: \mathcal{X} \subseteq R^n \rightarrow R, \; y \in \mathcal{Y} \tag{2}$$

The use of kernel functions is especially important in classification tasks when the samples from different categories are not linearly separable in their original feature space $\mathcal{X}$. In this case, a non-linear SVM should be employed, which in essence involves mapping the data in a higher dimensional feature space, where the data may be linearly separable, and derives the optimal separating hyperplane in this higher dimensional feature space. The increased computational complexity involved by an explicit computation of the data mapping to the higher dimensional space may be avoided through the use of kernel functions, as explained in detail in the literature, leading to the simplified form of decision functions from (1), regardless the dimensionality of the new feature space where the hyperplane actually resides [26, 27]. Many kernel mapping functions can be used, but a few kernel functions have been found to work well for a wide variety of applications, as the Radial Basis Function (RBF kernel) and the polynomial kernel, defined by the expressions:

$K(\mathbf{x},\mathbf{x}_i) = (G\mathbf{x} \cdot \mathbf{x}_i + C_0)^d$ - for the polynomial kernel

$K(\mathbf{x},\mathbf{x}_i) = \exp(-G|\mathbf{x}-\mathbf{x}_i|^2)$ – for the RBF kernel,

where $\mathbf{x}$ is the sample to be classified (represented as a vector in the n-dimensional feature space), $\mathbf{x}_i$ is any training vector represented in the same feature space, and G, C_0, and d are the parameters of the kernel functions, which should be tuned during SVMs training to achieve optimal accuracy and generalizations estimates for the classification problem.

Another important parameter that can control the SVM performance, in the case of the so-called "soft margin" SVM classifier, is the cost C that controls the trade off between allowing training errors and forcing rigid margins [24]. Increasing the value of C increases the cost of misclassifying points and forces the creation of a more accurate model that may not generalize well, leading to a hard-margin SVM. Decreasing C too much could affect the classification accuracy; therefore its tuning is often essential for the success of the resulting classifier scheme [25].

V. IMPLEMENTATION AND TESTING STRATEGIES

A. Classification approach

Currently there are several eye color classification scales used in the makeup industry. Generally, a three category eye-color classification (blue, green, brown) will do fine for amateur makeup, but for a professional one, the hues, tones (cold, warm) and brightness (light, dark) of the eyes will matter more. For instance, green eye colors can go from blue-green (cold-light/cold-medium colors) to brown-greens, also called hazel eyes (warm-light/warm-medium colors).

One of the classification scales we used is a combination of two types of labels, with values in the sets {Warm, Cold, Hybrid} and {Light, Dark, Medium}. In this type of description, the eye color is characterized by a pair of attributes, one from each set, yielding nine possible 'Eyes Harmony' "labels". The labeling of the global 'Face Harmony' was done by a makeup artist on the Database "PUT Face" of Poznan University of Technology, Poland [15]. This database contains 10000 pictures of 100 persons, 100 face positions for each person, from which we have chosen two positions that highlight mostly the eyes. From here, we have used the labeling done for the eyes in terms of the warmth and brightness of the eye color.

Regarding the 'Eye Harmony', the 100 instances are not well balanced, having more than a half of data labeled as ColdLight. The actual labeling of the 100 individuals in the PUT Face database in respect to the 'Eye Harmony' color classification scale is as follows: 5 individuals in the class Warm-Light; 9 individuals in the class Warm-Dark; 19 individuals in the class Warm-Medium; 54 individuals in the class Cold-Light; 5 individuals in the class Cold-Dark; 8 individuals in the class Hybrid-Medium. In practice, some of the combinations of warmth and brightness labels are very rarely encountered; in our case, having a rather reduced dataset, only six of the combinations of labels are present.

The cases where we would have Cold-Dark/ Cold-Medium / Hybrid-Dark (black, dark-blue, dark-green eyes) or Warm-Hybrid (amber) are quite rare, and a label as Warm-Light (yellow amber) is rare even in real-life. Therefore we have come to the conclusion that six or five classes of eye colors will cover the majority of the population.

As the experimental results weren't very promising with make-up artist settled labels, we also consider a more "standard" color classification scale for verifying the accuracy of eye color classification on this database. The proposed classification scale is based on the perceived iris color, and considers the definition of six classes, to which the 100 individuals in the database were assigned as follows: 34 individuals in the class Blue; 21 individuals in the class Blue-Green; 15 individuals in the class Brown-Green; 13 individuals in the class Brown; 7 individuals in the class Dark-Brown; 10 individuals in the class Gray-Hazel. These classes overlap mostly with the other nine classes obtained from combination of Lightness-Warmth indicators, namely: Blue eyes correspond to Cold-Light and Cold-Medium, Blue-Green eyes to Hybrid-Light and Cold-Light, Brown-Green eyes to Warm-Light and Warm-Medium, Brown eyes to Warm-Medium and Warm-Dark, Dark-Brown to Cold-Dark, Gray-Hazel to the rest of the classes.

We should note that, although Dark Brown eyes (commonly named "Black" eyes – corresponding to Cold-Dark combination) are predominant in African, American-Latino and Asian populations, they are not present in the PUT Face database, being probably not specific to the population sample used for its creation. This is why we excluded this class from our experiments.

Some example irises extracted for each class encountered in the PUT Face database are shown in Fig. 2.

Fig. 2. Samples of irises extracted for color classification: from up left going right and down, the shades go from darkest blue through different mixes of blue-green-brown, to dark brown shades.

B. Features extraction methods

The features extraction process, described in the previous section, requires the extraction of the iris area from a face picture; this was manually performed. For each individual in the database, we chose 2 pictures and we took into consideration all 4 irises available in these 2 pictures. Only the pixels corresponding to the iris were taken into account. As all the classification was done using the Libsvm Matlab tool, the training and test sets were written in the form of a feature vector preceded by the corresponding label for each instance. As explained earlier, different normalized linear histograms in the HSV color space were examined as feature spaces. Some tests were done considering all 3 components (Hue, Saturation and Value) and other tests were done using combinations of only 2 components: from all the combinations, the HSV combination proved the best suited for our classification, followed shortly in results by the HS combination.

Concatenated H,S and V histograms

In this case, the feature vector describing each instance (individual in the database) is simply the concatenation of the Hue, Saturation and the Value normalized linear histograms, quantized on n_{Bins}. Several values n_{Bins} were considered, in order to have a good balance between the classification accuracy and the feature space dimension.

N-D Histogram for N-components (N = 1, 2, 3)

Another way to represent the features vector was to obtain the multi-dimensional histograms, describing the co-occurrences of different quantized H, S and V values in the iris area – all of them or combinations of two color components only being considered. This form of histograms correlates more the appearance of each possible combination of H, S and V among the considered pixels. The 3-D plots of the co-occurrence histograms over the (Hue, Saturation) plane are shown in Fig. 3 and Fig. 4, for the two types of classification scales.

VI. Experimental results

The first set of experiments was done using the classification scale of the make-up artist, given by the warmth and the brightness of the color of an eye, as described in the previous section. The second set of experiment was done on the classification scale that we proposed: {Blue, BlueGreen, BrownGreen, Brown, DarkBrown, GrayHazel}. We made some tests with a five-colors system, unifying the Brown and DarkBrown shades, as the darkest brown shades in the PUT Face database wasn't actually well represented.

The two sets of experiments were run on the different HSV histogram based feature spaces (with different number of quantization levels) described above. We used the SVM classification tool developed for Matlab – LibSvm-3.11, which allows the computation of the optimal SVM classifiers parameters. The tests show that the RBF kernel is sometimes better than the polynomial kernel for our classification problem; this explains the choice of the RBF kernel for our experiments. The training set and the test set were generated from the PUT Face database iris images, by splitting the image data in half.

The experiments results in terms of classification accuracy in the test set, on the PUT Face database, in the various scenarios mentioned, are shown in Table 1 and Table 2. It is easy to observe that the results are quite close from one scenario to another, and in most of the cases, the best accuracies achieved can be considered satisfactory high. A summary of the best accuracies achieved in respect to the two classification scales, for the various feature spaces considered, is shown in Fig. 5.

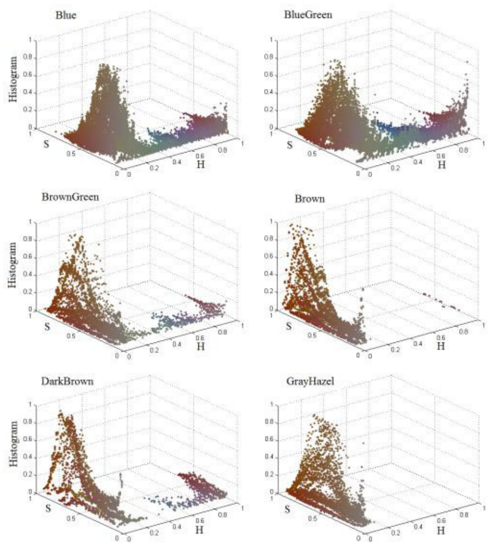

Fig. 3. The (Hue, Saturation) plane normalized linear histograms, grouped by 'Eye Color' classes

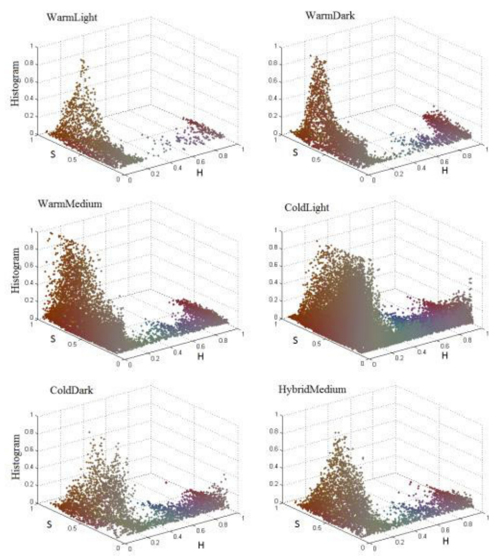

Fig. 4. The (Hue, Saturation) plane normalized linear histograms, grouped by 'Eye Harmony' classes

Table 1. Results for different types of tests - *'EyeColor'*

Vector type	Nr of bins/comp.	Accuracy (%)	Best C and G parameters of RBF Kernel
HSV concatenated vector	16	**100**	C=8, G=1
	32	**100**	C=8, G=0.5
	64	98	C=8, G=0.25
3-D histogram HSV vector	16	98	C=8, G=0.5
	32	**98**	C=8, G=0.125
2-D histogram SV vector	16, 32, 64	**98**	C=8, G=0.0625
2-D histogram HS vector	16	94	C=8, G=2
	32	96	C=8, G=1
	64	96	C=8, G=0.125
2-D histogram HV vector	16, 32, 64	90	C=8, G=0.125

Table 2. Results for different types of tests - *'Eye Harmony'*

Vector type	Nr of bins/comp.	Accuracy (%)	Best C and G parameters of RBF Kernel
HSV concatenated vector	16	92	C=8, G=2
	32	96	C=8, G=2
	64	92	C=8, G=2
3-D histogram HSV vector	16	94	C=8, G=0. 5
	32	94	C=8, G=0.125
2-D histogram SV vector	16	96	C=8, G=1
	32	92	C=8, G=1
	64	96	C=8, G=0.0625
2-D histogram HS vector	16	92	C=8, G=2
	32	**100**	C=8, G=2
	64	92	C=8, G=2
2-D histogram HV vector	16	92	C=8, G=2
	32	94	C=8, G=1
	64	94	C=8, G=0.25

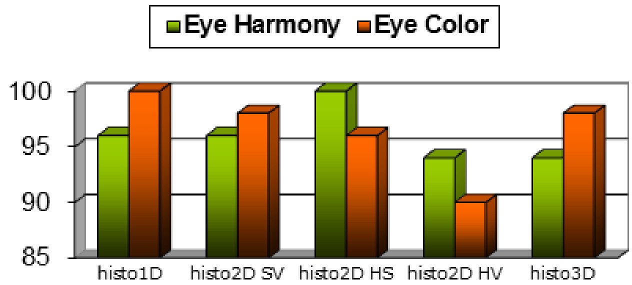

Fig. 5. Summary of the best accuracies (best SVM classifier) for the two classification scales, in terms of the different feature spaces considered

To compare our results with existing state of the art systems, let us consider e.g. the solution proposed by Dantcheva et al. [20] for the eye color classification (however not for cosmetics, but for biometrics) - where the eye colors are classified in 4 classes (Black, Brown, Blue, Green) with Gaussian Mixture Models in RGB space. Their results vary as accuracy from 81% for green to 100% for black and brown in the case of manual segmentation of the iris, which is overall below the rate of our system.

VII. Conclusion

This paper proposes a computationally simple and reliable way to classify the eye (iris) color according to the criteria used in cosmetics for the eye makeup. Such a stage is very important for the development of automatic makeup software that should suggest the right color combinations for a given face. The results, assessed in terms of the correct classification rates under two different eye color grading systems, are promising, being above the state of the art in the literature. However more tests should be performed in order to validate and select the optimal configuration on a larger database, once the ground truth provided by cosmetics experts will be gathered.

Representing the eyes as a combination of Hue, Saturation and Value gives very good classification accuracy, keeping in mind that a balance has to be found in terms of the quantization of the color components.

In our future work, we will focus on the extension of such an analysis to the other relevant facial features (hair and skin) and include the resulting classification modules into an expert system able to assess the 'Global Harmony' of the face and to apply it in building an automatic assistant for the whole makeup process.

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