ICA Analysis of Face Color for Health Applications

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Abstract

Continuous health status updates can be useful in providing warning signs for health problems, especially in caring for aging populations. Techniques in computer vision and statistical analysis can provide a way to automatically and remotely evaluate certain aspects of a person's health condition. This paper describes a method for using Independent Component Analysis to analyze face color to identify potential problems. This method can be implemented using a low-cost web camera combined with available open-source libraries.

Introduction

Computer vision when combined with other technologies is a very powerful tool for monitoring a person's health condition. Past research has shown applications in fever detection (Chan et al. 2004), driver fatigue (Zhu 2004), dentistry (Hammond et al. 2003), and radiology. In the paper "Hepatitis Diagnosis Using Facial Color Image", a machine learning algorithm was used to process images of jaundiced patients, and attempt to classify them based on RGB values of a sample of pixels (Liu and Guo 2007). Further, Tsumura (Tsumura, Ojima, and Sato 2003) shows that the decomposition of skin color using independent component analysis produces two components that could be identified as resulting from melanin and hemoglobin.

This paper specifically examines *independent component analysis* as a method to analyze patches of skin for anomalies. Changes to skin color can be a symptom of various different diseases. The conditions of skin whitening and darkening, as well as excess red, blue and yellow color can all indicate underlying health issues that require medical attention. By providing a quick way to remotely check for these skin conditions, they can be identified cheaply and easily.

In this project, ICA is used to isolate the melanin and hemoglobin components of skin color from a set of facial images. These components are shown to be consistent and stable between subjects of various skin tones and temporally consistent for each subject when no health affecting changes occur in the subject. Further, it is shown that conditions that affect skin tone can be identified systematically.

Additionally, because a third component was found resulting from reflective glare off the surface of the skin, we investigate techniques for removing the noise in order to better determine the contributions of the pigment components. We investigate a color subtraction technique as well as treating the reflective glare as a third component.

Finally, we consider future work necessary for operationalizing this concept. In order to further this study, more data will be required. This current work is preliminary to a larger study that will provide opportunity for collecting more data.

Color Model

In Tsumura's paper "Independent-Component Analysis of Skin Color Image", the color model used assumed that the reflected color from a person's skin was due almost completely to the two pigments melanin and hemoglobin (Tsumura, Haneishi, and Miyake 1999). The color vector was therefore decomposed into two independent components, one for each pigment.

Where Tsumura used this property to synthesize an image, in this project we use the decomposition approach to analyze skin color for both the hues of the two pigments and their quantities. Experimentally, we found that there was also a third component, most likely due to reflections from skin oils, which distributed itself into the two components. To account for this noise, we therefore describe our color model as follows:

Let $\mathbf{H}$ be the independent component (vector) corresponding to hemoglobin, and $\mathbf{M}$ be the independent component corresponding to melanin. The color vector of any skin pixel is the linear combination of those two components where q_H and q_M are the respective quantities of the two pigments in the pixel and r is some remaining baseline color (i.e. the noise).

$$[q_B, q_G, q_R] = q_H H + q_M M + r \tag{1}$$

While the key problem in this paper is to find the original signals, $\mathbf{H}$ and $\mathbf{M}$ and their quantities, given a set of skin pixels, one issue is to determine how to handle the reflective noise. To address this issue we follow two basic approaches in this paper. The first assumes that hemoglobin contains only red and blue components, while melanin contains only red and green components. We can factor the hemoglobin

and melanin vectors into two equations.

$$\mathbf{H} = [q_B, 0, q_R] + r_H[1, 1, 1] \quad (2)$$

$$\mathbf{M} = [0, q_G, q_R] + r_M[1, 1, 1] \quad (3)$$

where $[1, 1, 1]$ is the gray part of the independent component due to reflection of the white background lighting, and r_H and r_M are scalars which represents how much white is attributed to each independent component.

This decomposition is supported by the data samples gathered over a period of a few weeks. While the actual color vectors varied significantly even with measurements taken minutes apart, the hue stayed fairly constant, suggesting that when the effects of glare are taken out, the color vectors do not vary significantly. However, this scheme might turn out to be not completely applicable in the case of unusual melanin or hemoglobin components and might result eventually in the missing of change indicators.

To address this, our second approach we treat glare as an additional component and follow a basic paradigm where this noise component is identified based on the best reproduction of the overall color pixel distribution. Here we rely on the assumption that the variation between pictures taken in close proximity will likely be largely caused by changes in glare (i.e. noise) and not in the hemoglobin and the melanin components. To further investigate this we propose in our future work to enhance this effect by varying illumination parameters and thus explicitly causing changes in the distribution of the glare component.

Effects from Disease

Using the color model described, variations in skin color resulting from disease can be separated into two categories:

- Color vector: yellowing, blueness
- Color quantities: paleness, flushing, darkening

In the first case, we would expect yellow and blue to be absorbed into either the melanin vector, hemoglobin vector, or some of both. In the second case, we would expect the quantities of hemoglobin and melanin to change, but the color vectors should remain mostly the same.

Methodology

The goal of this paper is to describe a technique for determining the hue of the two aforementioned pigments and to determine the contribution of each pigment to the resulting color. As the contributing distribution of each pigment is unknown, the first challenge is to separate the two pigments from the given image. The next challenge is to remove the effects of noise. Then, we can proceed by analyzing hue and the quantities. The process is shown in Figure 1 and is summarized as follows:

1. data acquisition
2. primary signal separation
3. noise separation
4. hue analysis
5. source quantification

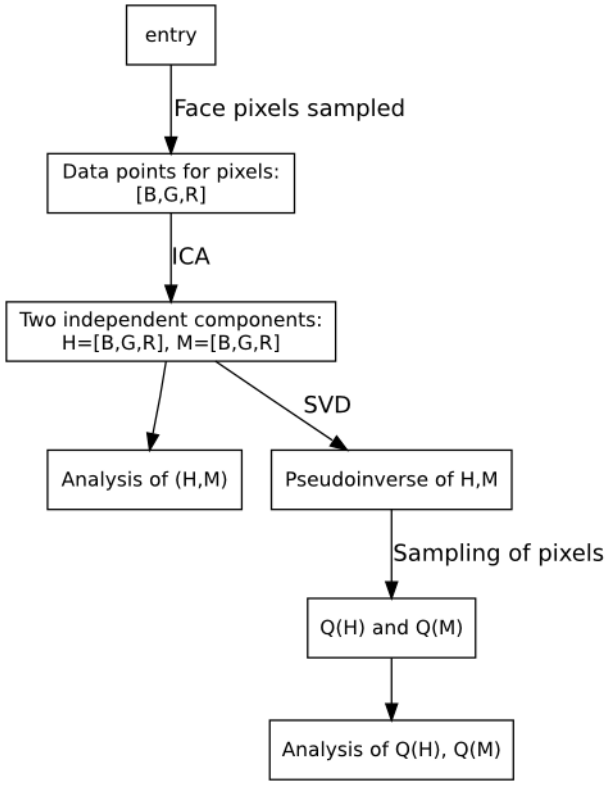


Figure 1: Process overview

Data acquisition: This part of the process addresses image capture and representation. Capture is generally a matter of implementation. Once an image is captured and the appropriate pixels are identified, these samples are stored as $n \times 3$ matrices for n pixels.

Primary signal separation: The process of separating the primary signals from the mixed signals is accomplished by *independent component analysis*. The result is two component that are statistically independent. These components are key elements of the overall analysis.

Noise separation: Experimentation shows that there is a white component resulting from reflection on the surface of the skin. This noise must be separated from the two components. This is accomplished using one of the two proposed methods, either assuming zero blue and green components for melanin and hemoglobin, respectively, or by finding the minimum of the variance of their mean ratio across three images assuming varying glare components.

Hue analysis: The resulting vectors can be used to find the hue angle. This is done separately for each pigment component.

Source quantification: Once noise has been handled and the independent component stabilized, the contribution of each pigment to the resulting image can then be found. We use the pseudoinverse of the matrix formed from the independent components, applied to each pixel, to find the mean quantities of the pigments contributing to the overall color.

Independent Component Analysis

As a generative latent variable model, *independent component analysis*, gives a representation of multivariate data with non-Gaussian latent variable distribution. Because we cannot assume that the image data is normally distributed, this approach is preferred over *principal component analysis* which only guarantees linear independence if the latent variables have joint Normal distribution. ICA assumes that the distribution of the latent variables is non-Gaussian and uses that to find independence in the components. Summarily, the ICA algorithm finds a representation of data such that the linear independence of the individual components is maximized. This property addresses this paper's central problem of blind source separation. The *Cocktail-party problem* is a classic example of the signal separation problem and is described in (Hyvärinen and Oja 2000). In this present work, signal separation and ICA relate to the problem of determining the mixture of pigment contributions to the color of a patch of skin.

In the given color model, we have assumed that the color of the skin is a linear mixture of two sources (melanin and hemoglobin) (Tsumura, Haneishi, and Miyake 1999). See Equation (1) above. Given that, we consider each pixel in an image of a subject's skin as a set of n linear mixtures $\mathbf{x} = x_1, ..., x_n$ of two independent components.

The task here is to recover the original signals s_n for both pigment contributions. As described in the color model, we assume noise in the signals from residual articles (e.g. glares, oil on the skin, etc.). For the sake of discussion, we approach the noise separately and show the simple case of ICA. In matrix form, this is shown in Equation (4) where $\mathbf{x}$ is the mixture vector (the pixel in our problem), $\mathbf{s}$ is the original signal vector (hemoglobin and melanin), and $\mathbf{A}$ is the mixing matrix.

$$\mathbf{x} = \mathbf{A}\mathbf{s} \tag{4}$$

In general, several techniques are available to solve for the source signals (Comon 1994). In principle, these methods seek a matrix $\mathbf{W}$, as the inverse of the estimation of matrix $\mathbf{A}$, such that each s is independent:

$$\mathbf{s} = \mathbf{W}\mathbf{x} \tag{5}$$

As implemented in this work, for each image captured, a set of n pixels is stored as an $n \times 3$ matrix, where each pixel is represented as $[q_B, q_G, q_R]$, with $0 \leq q_B, q_G, q_R \leq 255$. The FastICA algorithm (Hyvärinen and Oja 2000) is then used to acquire sets of independent components, two based on each image.

Because ICA does not provide an ordering for the components returned, each independent component is matched against prototype components for hemoglobin and melanin and labeled as such.

$$\begin{bmatrix} M_B & M_G & M_R \\ H_B & H_G & H_R \end{bmatrix} \tag{6}$$

Analysis of color vectors

To analyze the color vectors, the hue angle (see Preucil's color circle (Preucil 1953)) is calculated for each component as follows:

$$\begin{aligned}
\text{for } R \geq G \geq B,\ \mathrm{h} &= 60 * (G - B)/(R - B) \\
\text{for } G > R \geq B,\ \mathrm{h} &= 60 * (2 - (R - B)/(G - B)) \\
\text{for } G \geq B > R,\ \mathrm{h} &= 60 * (2 + (B - R)/(G - R)) \\
\text{for } B > G > R,\ \mathrm{h} &= 60 * (4 - (G - R)/(B - R)) \\
\text{for } B > R \geq G,\ \mathrm{h} &= 60 * (4 - (R - G)/(B - G)) \\
\text{for } R \geq B > G,\ \mathrm{h} &= 60 * (6 - (B - G)/(R - G))
\end{aligned}$$

In practice, we found that the hue angles for these pigments for most people under normal conditions were ≈ 60 for melanin, and ≈ 330 for hemoglobin. Variances in apparent skin color are accounted for in the quantity/saturation of the pigments.

Experimentation shows that when the lighting conditions is held relatively constant, the hues remain extremely stable, suggesting that if images are taken over time in the same location, variations in hue will be fairly easy to detect. This can be expected to remain the case even accounting for noise as long as the noise is consistent.

Source Quantification

In order to determine the ratio of quantities of the two components, the Moore-Penrose pseudoinverse (using Singular Value Decomposition) of each component is found. This inverse is applied to each pixel in the original image to get the average quantities of the independent components. These averages are normalized as follows:

Let $\hat{q}_H$ and $\hat{q}_M$ be the average quantities of the hemoglobin unit vector and melanin unit vector. It is possible that some of the q_H and q_M are negative, in which case we shift the entire distribution so all points have positive q_H and q_M. In this way, we estimate the residual color and shift the distribution to minimize its effect.

We assume there is a point with lowest melanin, and one with lowest hemoglobin that we can use as a baseline. By shifting the distribution such as to make these points have positive quantities, we can now look at the ratio of q_H and q_M.

We can interpret this ratio as the number of units of q_H which appear with an additional unit of q_M, and use this to identify the health conditions which could cause an excess or a lack of the quantities of hemoglobin or melanin.

Handling the white component

Because there is an uneven distribution of reflection in hemoglobin and melanin, we must find the amount of that noise in each of the components individually. This uneven distribution is caused by physical arrangement of the two pigments in the skin. Melanin is situated in the epidermis, closer to the surface of the skin, while hemoglobin is predominant in the dermis.

To determine the amount of white distributed into each component, we propose two approaches here. In the first the noise is determined by subtraction assuming that the melanin and hemoglobing components have zero blue and green components, respectively. In the second, we only assume the components to be stable and that the noise will

have some variance across the three acquired images. The key task is then finding the quantities of white noise in the other components that best explains the variance. These are expressed as q_H and q_M in Equation (1).

This can be accomplished by finding the minimum variance of the ratio of the mean quantities of the components across the acquired images with respect to q_H and q_M. A brute force method of iterating through a range of values for each components is used. Starting from base values, white is added back to each component individually and the variance across images found.

Separating out quantity by subtraction If we assume that melanin only contains green and red components, and hemoglobin only contains blue and red, we can just subtract out some quantity of color such that the melanin has no blue component left, and that the hemoglobin has no green component left. Then, we can calculate the pseudoinverse and proceed with taking the ratio of the two quantities.

Therefore an independent melanin component $[M_B, M_G, M_R]$ becomes $[0, M_G - q_B, M_R - q_B]$, and in the vast majority of cases, $M_G > M_B$ and $M_R > M_B$ so the component is still positive. Similarly, the independent hemoglobin component $[H_B, H_G, H_R]$ becomes $[H_B - q_G, 0, H_R - q_G]$, and once again the component was usually positive. The resulting matrix to perform pseudoinverse on becomes

$$\begin{bmatrix} 0 & M_G & M_R \\ H_B & 0 & H_R \end{bmatrix}$$

where M_G and M_R are the green and red components of melanin with B subtracted, and H_B and H_R are the blue and red components of hemoglobin with G subtracted.

Separating out as a third component If we assume that reflections are a component, we can pass a $[1, 1, 1]$ along with our two independent components before calculating the pseudoinverse. This may introduce new error, since ICA was run on the points with the assumption that there were only two independent components . In this case, the resulting matrix becomes:

$$\begin{bmatrix} M_B & M_G & M_R \\ H_B & H_G & H_R \\ 1 & 1 & 1 \end{bmatrix}$$

Both of these methods were tried, and results were mixed. Although it appeared that in most cases flushing and paleness were reflected in the ratios, the quantities' variance from a live feed was quite large, suggesting that some other method should be used to stabilize the quantities. In (Tsumura, Haneishi, and Miyake 1999), reflections were not factored into the two components, and it was noted that when more pigment was added, the amount of reflection also increased. To make the third component method more robust we propose to use active lighting variations to increase the glare variance without affecting the melanin and hemoglobin components.

Experimentation

Two forms of experimentation were performed. The first set utilized static images of people with known health conditions. The second set were captured live from an inexpensive web camera mounted behind a two-way mirror.

Static images

Changes to the color vector We performed tests on static images of patients with two conditions known to affect skin color; Argyria and Gilbert's syndrome.

Argyria is a skin condition caused by exposure to silver in which the skin turns blue-gray. An image of an Argyria patient from a news website was analyzed and compared to that of the same patient before the silver exposure. We would expect to see this blue-gray component absorbed into either hemoglobin or melanin, changing the color vector.

	Normal	Argyria	Jaundice
Melanin			
	60	240	60
Hemoglobin			
	330	330	120

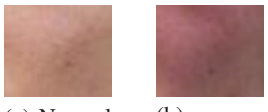
Table 1: Example changes in hue

Gilbert's Syndrome causes jaundice in sufferers from excess bilirubin produced in the blood. Bilirubin is a yellow product, and therefore the skin condition of jaundice is characterized by excess yellow component in skin color. We would expect to see yellow absorbed into one of the independent components, changing the angle of the color vector.

Static images of patients with these conditions were analyzed. The resulting hues indicated a significant change in the color vector of individual components. Table 1 shows the results of these color changes with respect to a subject in normal conditions.

Changes to color quantity Changes to the quantity of the colors are less straightforward to interpret. Since the independent components contain some amount of reflected light, this could affect the quantity of the vectors. Since the color model assumes that reflections are uniformly distributed over the face, the two components should contain equal amounts of white vector.

For subjects with similar lighting and color vectors, the hemoglobin/melanin ratio values can be used as a measure of redness. In the following sample images, one normal and the other flushed, the ratio increased from 1.1 to 1.2.



(a) Normal skin (b) Flushed skin

Figure 2: Static images of skin patches

Live capture

Skin patch acquisition In this project, when sampling from a live feed, pixels were taken from both cheeks of the user's face to provide the data points for ICA. Using the cheeks to provide the pixels to be analyzed can guarantee a consistent and unobstructed patch of skin in subsequent trials. There are many face detection algorithms which can be used to get a bounding box for the cheeks. We used Viola and Jones' (Viola and Jones 2004) method of Haar Cascades to identify the mouth and eyes, and then the cheek boxes were estimated from these bounding boxes as shown in figure 3.

The cheeks are assumed to be a rectangle of the same width as the eyes, extending to touch the top of the mouth. The middle of the cheek was taken to avoid overlap with the background or parts of the nose.

In this way, objects like glasses or hair which can distort the distribution of the pixels are kept out of the skin patch. For our experiments, around 2000 pixels were captured for each sample.

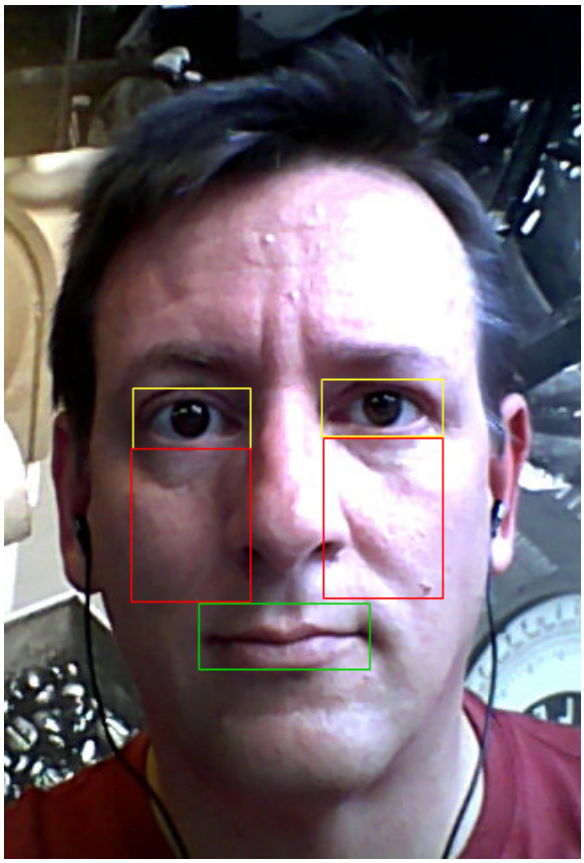


Figure 3: Sample bounding boxes

Image sets Two sets of images were acquired and analyzed from an inexpensive web-camera mounted behind a two-way bathroom mirror with a uniform lighting system. The purpose of the first set was to show stability in color vectors and quantities across multiple days. It contained images for seven (7) subjects. For each subject, three images were taken daily over a period of five (5) days. These images were taken at different times of the day and at different physical stances naturally. We expect there to have been some variation in noise resulting from slight differences in ambient lighting.

A second set contained images of five (5) subjects. For each subject, three baseline images were taken. Then, attempting to induce a flushness by raising heart rate, each subject exercised for some period. Three more images were then taken of each subject.

Results in color vector and quantity From images captured across five separate days, these images containing slight variations in ambient lighting and shading, the independent components maintained consistent across the images. The hue resulting from the color vector of each component, therefore, remained the same across days at melanin ≈ 60, hemoglobin ≈ 330.

On the other hand, the average quantities that each pigment contributed to the resulting pixels varied from day-to-day for each subject and also between subjects. Table 2 shows the standard deviations for each subject.

subject	standard deviation
1	0.22
2	0.12
3	0.13
4	0.62
5	0.29
6	0.46
7	0.81

Table 2: Standard deviations across days

The standard deviation of the ratio of quantities across all individuals for the given five days was $\sigma \approx 0.52$. In the second data set, the components stayed similarly constant while the quantities seemed to indicate a systematic hemoglobin increase for the flushed condition. However, the differences proved not to be statistically significant across baseline and flushed images in the second set ($\sigma \approx 0.06$). This could be due to the incomplete noise removal or the relatively low level of exercise that was used in the experiment.

Results in removing the white component Because the three images captured from a live subjects were taken moments apart, there was little change in the lighting on the subject's face between the images. This was indicated in no detectible difference in the variances of the component quantity ratios between the three images. While we assume there to be some variance, such difference may have been too small for the precision used in the calculation.

Conclusion

Using ICA to separate out the hemoglobin and melanin components of a person's complexion may be a fairly simple way to check on the health of a person. These measurements can

be taken at home with relatively inexpensive equipment and the algorithms involved are fairly common and implemented by multiple open source libraries.

When running this analysis on static images, we found that the hue angles of the two components were overall very stable for repeated samples of the same person, and were sensitive to changes in the color vectors brought on by discoloration of the skin due to disease.

The quantities obtained by taking the pseudoinverse of the two components were moderately stable, but error was introduced into the measurement by the presence of reflections. Various methods of compensating for the reflections gave mixed results for improving the stability of the quantities.

For analysis on images taken by a web-camera, hue angles continued to exhibit the same stability. This is expected behavior. Quantities, however, varied across subjects and across days for the same subjects. This may be an effect of the image acquisition process as no control accounted for lighting, pose in relation to the camera, nor for the physical condition of the subjects. It is interesting to note that the ratios did change in the same direction, however insignificantly, between baseline and flushed images. This matches with the result in the static image.

These results indicate that it is possible to detect changes in hue and in the ratio of the quantities of each component. While experimental data may not support the stabilization of the two pigment components, the methodology is fundamentally sound. As such, we have shown that *independent component analysis* is a viable method for decomposing images of skin into a usable data set for monitoring skin tone and, ultimately, the health of a given subject.

Further Work

Automation

For use in a live scenario within a home or apartment, image capture and processing will need to be automated. To automate image capture, facial recognition will be introduced so that trends for individuals may be recorded. For processing, a statistical distribution could be associated with the past and present hues of a user's face, and deviations could be calculated automatically. Machine learning algorithms have been shown to be effective in estimating the progression of the underlying disease based on how jaundiced the skin color was, and their use could be extended to cover not only changes in the color component, but also the quantities of each component. Trends over time could be observed, and estimations could be made about which deviations were significant, and which reflected everyday variability.

Variance in lighting

Future work also will need to address the normalization of the two color vectors to take into account the uneven distribution of the reflection (white) color vector between the two independent components. One method to be explored is systematically inducing variation in the distribution of the lighting between the three images. LED lighting can be easily controlled programmatically and synchronized with the image capture process.

Other areas of the light spectrum

Finally, infrared photography may provide a third dimension of information which could be integrated with the previous results. The amount of reflectivity, which increased error for our measurements, could also be analyzed for details about how oily the user's skin is or the presence of perspiration present.

Acknowledgments

This material is based upon work supported by the National Science Foundation under Grants CNS-0649229 and CNS-1157061.

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