

Interpretation of Polarization-Encoded Images Using Clustering and Lab Colour Space

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Abstract: Physical interpretation of polarization-encoded images is not obvious since the information content is intricately combined in the channels of this imaging modality. Thus, the need for a proper tool that allows the analysis and understanding of polarization-encoded images is of prime interest. In this paper, a novel mapping is proposed between the Poincaré space and a parametric color space where an adequate distance is defined and used in the fuzzy C-means clustering algorithm for classification issues. Moreover, the obtained label map is used as a priori information to provide an ad hoc colour display, which allows a proper interpretation of the resulting colored image at a glance.

Key-Words: - Polarization-encoded images, Stokes parameters, Lab color model, Lab clustering, Fuzzy C-means segmentation, Color representation.

1 Introduction

Polarization imaging consists of the distributed measurements of polarization parameters of light across a scene [1], [2]. That way, one defines the "Stokes imaging" as the bidimensional measurements of light's Stokes parameters impinging on the CCD camera. Four-component information is attached to each pixel in the Stokes image [3], which gives its multidimensional structure. Stokes channels provide a rich set of physical information about the local nature of the target, which make interpretation of such multidimensional structures hard to grasp at once. In this paper we address the problem of analyzing polarization-encoded images and explore the potential of this information for classification issues. A straightforward mapping is addressed between the Stokes space and a parametric color space with an adequate distance defined and used in the fuzzy C-means clustering algorithm for image segmentation [4], [5], [6]. The segmentation map is considered as a pre-processing of the image, allowing afterward the interpretation of the distribution of the physical information carried by the Stokes image. Lab (L : luminance, a (green to red), b (yellow to blue)) [7] color space is chosen, because equivalent to the Stokes parameter system, and more suited for describing in colors in terms that are practical

for a better analysis. Histogram equalization is applied also to each class of the channel associated to the luminance axis in order to preserve the information in the intra-class smooth variations. The proposed algorithm is applied and validated with Stokes images of a histological section of biological tissues

This paper is organized as follows:

In the second section, a brief definition of Stokes imaging is given. One defines also the Lab color model, and its mathematical representation. We carry-on in the third section, by the mapping formula between the Stokes system and the Lab color space, and the spherical representations of these two spaces are introduced. The segmentation method of the Lab image is also derived in this section, with the adequate distance used instead of the classical Fuzzy C-means distance. In the fourth section, the color algorithm used in order to interpret the multidimensional physical Stokes channels using a single color image is derived.

2 Background

In this section, one presents briefly the definition of the Stokes imaging and Lab color model used in this paper.

2.1 Stokes imaging

The design of imaging systems, that can measure the polarization state of the outgoing light across a scene, is mainly based on the ability to build effective Polarization State Analyzers (PSA) in front of the camera that permit to acquire the Stokes vectors corresponding to each pixel in the image [3]. It can be shown that four intensity measurements are needed in order to obtain the Stokes image. The reader is referred to [3] for more details.

The general polarization state of a light wave can be described by the so-called ‘‘Stokes vector’’ (SV) \mathbf{S} which fully characterizes the time-averaged polarization properties of radiation. It is defined by the following combination of complex-valued components E_x and E_y of the electric vector [8] in two mutually orthogonal directions x and y as

$$\mathbf{S} = \begin{pmatrix} S_0 \\ S_1 \\ S_2 \\ S_3 \end{pmatrix} = \begin{bmatrix} \langle E_x E_x^* \rangle + \langle E_y E_y^* \rangle \\ \langle E_x E_x^* \rangle - \langle E_y E_y^* \rangle \\ 2 \operatorname{Re}(\langle E_x^* E_y \rangle) \\ 2 \operatorname{Im}(\langle E_x^* E_y \rangle) \end{bmatrix} \quad (1)$$

where S_0 defines the total intensity, S_1 describes the excess of parallel to perpendicularly polarized light, and S_2, S_3 convey the nature and handedness, respectively, of the wave. It is straightforward to show that

$$S_0^2 \geq S_1^2 + S_2^2 + S_3^2 \quad (2)$$

where the equality holds for completely polarized radiations.

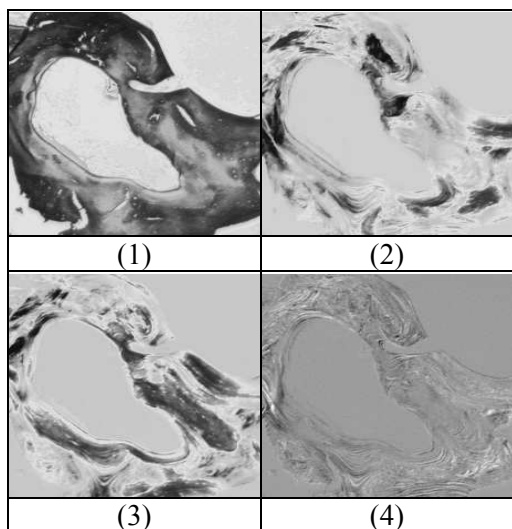


Figure.1 – S_0 (1), S_1 (2), S_2 (3), and S_3 (4) images of a histological section of a bone coloured with red picosirius and imaged at 650 nm wavelength. The image at the upper left is to be compared with a conventional intensity image.

Figures (1.1 to 1.4) represent the four Stokes channels images of a histological section of a bone coloured with red picosirius and imaged at 650 nm wavelengths. The image at the upper left corresponds to a conventional intensity image.

It can be shown that the normalized Stokes vector \mathbf{S}/S_0 has a geometrical representation. In fact it defines a single point that lies in a unit ball called the Poincaré ball [8], [9] as depicted in Figure.2.

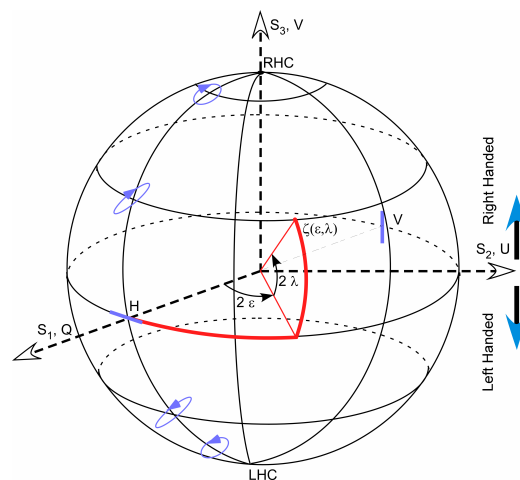


Figure.2 – Poincaré ball. Completely polarized light lies on the surface of the sphere. Partially polarized radiations lie inside the ball.

Each Stokes vector can be represented by point on the unit Poincaré ball. Thus completely polarized light lie on the surface of the ball, whereas partially polarized light lie inside the ball [10].

2.2 Lab color space

CIE $L^*a^*b^*$ (CIELAB) [8] is the most complete color model, used conventionally to describe all the colors visible to the human eye. The $*$ after L, a and b are part of the full name, since they represent L^*, a^* and b^* , derived from L, a and b .

It decouples the luminance component L from the colour-carrying information or chrominance (a and b). Each colour is described according to three physiological criterions:

- The a parameter is related to the position between red and green (negative values indicate green ($-a$) while positive values indicate red ($+a$)).
- The b parameter is related to the position between yellow and blue (negative values indicate blue ($-b$) and positive values indicate yellow ($+b$)).

The parameter L is an achromatic information and gives a measure of the brightness quantity in the color (bright to dark) ($L, L = 0$ yields black and $L = 100$ indicates white). The Lab color model has been created to serve as a device-independent, absolute model to be used as a reference. Since the Lab model is a three-dimensional model, that can only be represented properly in a three-dimensional space, it is mathematically represented by a three-dimensional sphere. Each axis of the sphere represents one parameter in the Lab color as illustrated in Figure. 3. A useful feature of the model however is that the first parameter is extremely intuitive: changing its value is like changing the brightness setting in a TV set.

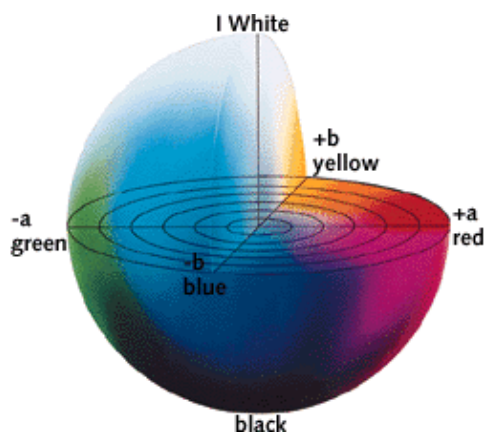


Figure.3 – Spherical representation of the Lab colour space

In this model, the color differences, which one perceives, correspond to distances when measured colorimetrically. The a -axis extends from green ($-a$) to red ($+a$) and the b -axis from blue ($-b$) to yellow ($+b$). The luminance L increases from the bottom to the top of the three-dimensional model.

3 Image segmentation

3.1 Poincaré ball to Lab space mapping

In order to process coherently the physical contents of Stokes images, one needs to handle all the channels at once by the processing algorithms. This can be done by using an adequate mapping of the Poincaré ball to the Lab space and using algorithm devoted to colour image processing. Let us note the normalized Stokes vector as

$\bar{\mathbf{S}} = \mathbf{S}/S_0 = [1 \quad \bar{S}_1 \quad \bar{S}_2 \quad \bar{S}_3]$. We define the transformations that map the Poincaré ball to the spherical coordinates of the Lab space as the arrangement of the normalized Stokes parameters in the Lab scale, in order to have a straightforwardly

equivalence between the unit Poincaré ball and the Lab representation. This transformation is done as follows:

$$L = 100 \frac{\bar{S}_3 - \min(\bar{S}_3)}{\max(\bar{S}_3) - \min(\bar{S}_3)} \tag{3}$$

$$a = (\max(a) - \min(a)) \frac{\bar{S}_2 - \min(\bar{S}_2)}{\max(\bar{S}_2) - \min(\bar{S}_2)} + \min(a)$$

$$b = (\max(b) - \min(b)) \frac{\bar{S}_1 - \min(\bar{S}_1)}{\max(\bar{S}_1) - \min(\bar{S}_1)} + \min(b)$$

where $\max(a)$, $\min(a)$ (resp $\max(b)$, $\min(b)$) are the values representing red and green colors (resp yellow and blue colors). Figure (4. $L - a - b$) shows the mapping result of the normalized Stokes image given in Figure. 1. The proposed mapping can be interpreted in the following manner:

Pixels luminance L reflect the handedness of the wave (right- to left-handedness are represented by dark to bright pixels), the parameters a and b are the normalized channels \bar{S}_2 and \bar{S}_1 respectively in the Lab scale. The choice of these attributions between the normalized Stokes space and Lab color space is done with respect to the X, Y, Z axes in the two spheres.

This mapping is merely the injection of the Poincaré ball in the Lab one, in order to process the resulting color images using adequate algorithms.

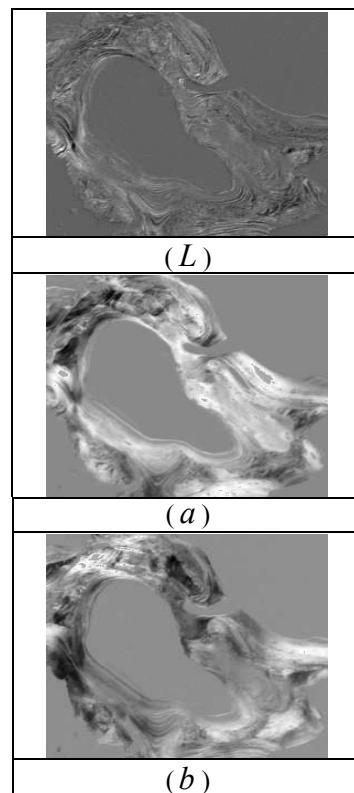


Figure.4 – Resulting Lab channels representation of the normalized Stokes image. L channel, a channel and b channel respectively from top to bottom.

3.2 Polarization-based clustering

The reason for using a clustering process is to classify the pixels of an image into different sets, each set corresponding to a specific physical feature in the imaged scene. Segmentation can prove a difficult task when the physical properties are intricately combined in each pixel location [11], [12]. Then, a coherent processing of the vector features is needed since segmentation based only on scalar values in each channel is almost impossible. Hence a clustering procedure is proposed, based on a polarization analysis of the scene via the mapping introduced in the preceding section.

Fuzzy C-means method is an efficient technique for segmenting multidimensional images [4], [5], and [6]. However, since in our case each pixel of the image corresponds to a point on the Lab sphere, it is thus more convenient to use a proper distance of a sphere. We define a distance between two pixels in the Lab image as follows:

Let $X_1 = [l_1, a_1, b_1]$ and $X_2 = [l_2, a_2, b_2]$ be two pixels in the Lab image. We call δ_1, λ_1 and δ_2, λ_2 respectively the latitude and longitude of X_1 and X_2 defined as:

$$\delta_i = \arctg \frac{a_i}{b_i} + \pi \mu_0(-b_i) \cdot \text{sign}(a_i)$$

$$\lambda_i = \arccos \left(\frac{l_i}{\sqrt{l_i^2 + a_i^2 + b_i^2}} \right) \quad (4)$$

for $i = 1, 2$. $\mu_0(x)$ is the Heaviside function, equal to 1 if $x \geq 0$, 0 elsewhere. $\text{Sign}(x)$ is equal to 1 for x positive, -1 for x negative and 0 for x null. Finally the distance between X_1 and X_2 is:

$$d(X_1, X_2) = 2R \arcsin \sqrt{\sin^2 \left(\frac{\delta_1 - \delta_2}{2} \right) + \cos(\delta_1) \cos(\delta_2) \cdot \sin^2 \left(\frac{\lambda_1 - \lambda_2}{2} \right)} \quad (5)$$

where R is the radius of the Lab sphere. This distance is the classical distance defined between two points on a sphere. Consequently, the Lab image can be clustered into k classes by using a fuzzy C-means algorithm after substituting its classical Euclidian distance by the distance defined in equation (5). Figure (5) shows the 4-classes label map obtained by using the clustering procedure introduced in this paper.

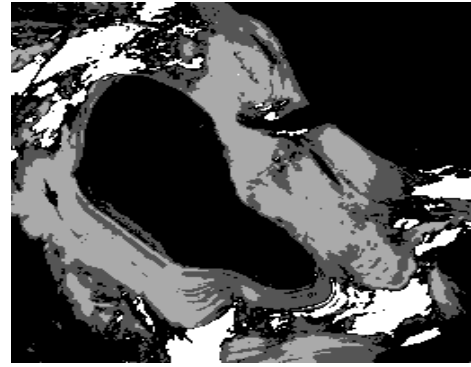


Figure.5 – Label map obtained with our clustering for 4 classes.

3.3 Color preview algorithm

Brightness variations inside each class are not well displayed in the L -channel image (Figure 4. L) since it reflects the variations over the whole image.

Here one employs a technique that uses the segmentation map obtained by the above-mentioned algorithm as an *a priori* information in order to allow, at best, a distribution of the information in the color space. This is done in the following way:

Once the label maps are obtained from the above mentioned algorithm, different masks corresponding to each class (C_k) can be used to extract sets of brightness values from the L -channel image. Histogram equalization is then performed over each set to redistribute uniformly the brightness values inside each class in order to reflect in the best way the intra-class variations. Each set in the L channel corresponds to one class (C_k) in the label map. The new brightness values are finally assigned to the L -channel. Figure (6) shows the result of the intra-class histogram equalization on the Brightness channel. One can see clearly the advantages of this processing by observing the smooth variation of the information content inside each physical feature represented by different classes as compared to the image in Fig. (4- L).

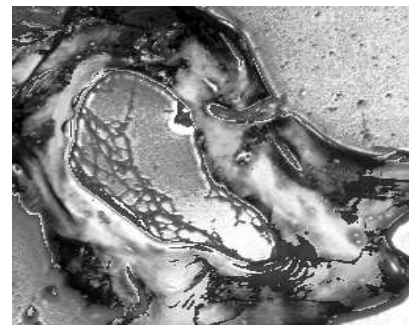


Figure.6 – L -channel image after histogram equalization corresponding to each class.

Finally, the three channels L , a and b can be used to generate an RGB colour image for display purposes. This is presented in Figure.7. The distribution of the colours in the resultant RGB image is a compact manner to represent the variation of the physical properties of the scene represented initially by four different channels, in one single image. In the resultant image each color corresponds to a physical information namely the absorption, the reflectance, the diattenuation, the retardance [1], [3]...etc, of the Stokes image which is not easily located in the above four channels.

The whole processing can be summarized as follows:

1. Normalization of the three last channels by the first one.
2. Poincaré ball to Lab mapping
3. Segmentation of the Lab image using the algorithm of section 3.2.
4. Equalization of the histograms corresponding to the pixels of each class in the L channel.
5. Replace of the old L channel by the new one obtained at step 4.
6. Lab image to the RGB image transform
7. Display the RGB image.

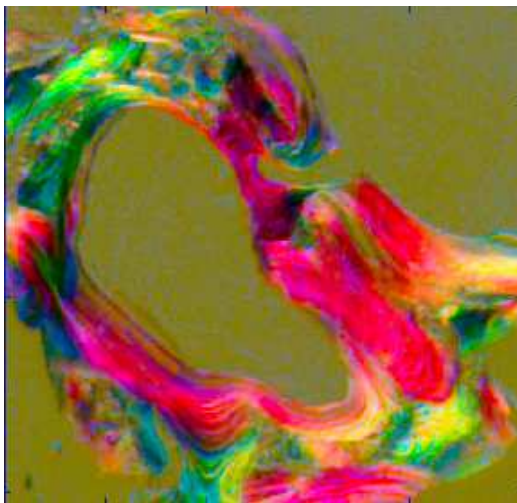


Figure.7– The combined result of the proposed clustering algorithm with our novel colour preview procedure. The image is for the red picosirius coloured histological section of a bone shown in Figure.1.

4 Conclusion

In this paper, a new method for interpreting physical properties of Stokes imaging was introduced. The major interest of this investigation comes from the interpretation of the physical properties of a scene using colors. The map of the Stocks image to Lab is a way for

the eye to distinguish the difference of characteristics of the image and to synthesize maximum information in a color preview that permits qualitative interpretation of the target properties in terms of physical contents. The main interest of the method is the use of the segmentation map in order to yield a colouring scheme that preserves the smooth variations of the physical content across the scene. The method was validated on Stokes images of biological tissues and an illustrative sample is shown here in order to appreciate the interest of the proposed method. The derived algorithm in this paper will be at the base of future challenges concerning the attribution of each color to exactly its corresponding physical property.

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