Liquid Crystal Image Analysis by Image Descriptors

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Abstract: Liquid crystals are substances with high impact technological, new substances have been discovered and the properties of these materials need to be examined. When viewed under a microscope using a polarized light source, different liquid crystal phases will appear to have distinct textures and colors. The use of digital image processing and computer vision is being initialized in the analysis of these materials. The goal of this work is to propose methods, based on visual descriptors, which are able to identify phase transitions and classify phases in liquid crystals from a sequence of images.

1 INTRODUCTION

Most substances are found in the following states: solid, liquid or gaseous. The process in which a substance changes from solid to liquid is defined as fusion. Besides it, there is a number of substances into an intermediate state showing simultaneously physical properties of liquids and features of crystals. This state is known as liquid crystalline and these substances are called as Liquid Crystals (LC). There are many different types of phases in this state, which can be distinguished by their different optical properties (Fig. 1).

When viewed under a microscope using a polarized light source, different liquid crystal phases will appear to have distinct textures and colors. In general, in a phase transition, the images have significant alterations related to optical properties. Such changes may occur due to several factors such as temperature and time. Physics researchers study phase transitions as a way to find alternative substances which have desirable properties (Bahadur, 1992).

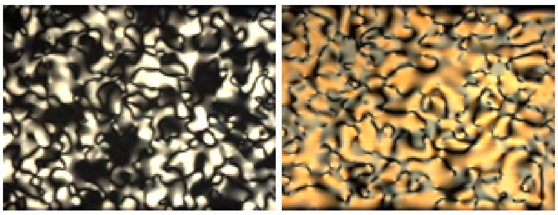

Figure 1: Examples of liquid crystals at different temperatures.

Light polarizing-microscopy provides a sequence of images which each image frame is acquired in a distinct temperature. The physical characteristics may be indirectly determined by image sequence analysis (Sampaio and C., 2004). Statistical approach is a way to do such analysis (Montrucchio and Strigazzi, 1998). This approach is simple to apply, however, some phase transitions are not clearly observed in such approaches, what justifies the design of more complex techniques.

The goal of this work is the proposal of two methods to solve problems in liquid crystal research field by application of Visual Descriptors, which are usually applied to accurate representation of images. Visual Descriptors may be designed to several computer vision applications; in this paper, Visual Descriptors are applied to extract structures from the liquid crystal images in order to make possible the measurement of features that could characterize phases and transitions.

The first proposed method consists in the application of Visual Descriptors as phase transition detectors for liquid crystal analysis. This method receives as input a sequence images of liquid crystal, makes calculations with visual descriptors and similarity measures and returns a graph where phase transitions can be identified. The second one is the retrieval of images from a sequence which are closer to an image parameter, which characteristics are used as key features for the search, as occurs in a typical Content-Based Image Retrieval (CBIR) system. The

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main characteristics extracted are related to color, texture, spatial relationships and shapes (Snoek, C. and Worring, M., 2005).

This paper is organized as follows: Section 2 presents some preliminary definitions. Section 3 introduces the method to detect phase transitions by application of Visual Descriptors. Experimental results are shown in Section 4 and Section 5 concludes the paper.

2 PRELIMINARY CONCEPTS

Content-based image retrieval (CBIR) systems search similar images based on their characteristics: their feature extraction algorithms obtain image properties using descriptors, and given a similarity function, they calculate the similarity between two images.

Two important features may be used to describe an image: color and texture. Color is widely used to represent an image, it maintains its properties when it functions as translation, rotation and scaling are applied the image. Texture is also an important property for characterization and image recognition, consisting in a simple assigment of a repeating pattern in which the elements are arranged (Cess, G., Snoek, M. and Worring, M. , 2005).

2.1 Color Moments

Color Moments are statistics moments of the distribution probability of the colors and have been used with success in image retrieval systems, specifically when the image contain only one object. The values of mean (μ), variance (σ^2) and standard deviation (σ) are color moments that have been proven to be efficient and effective in the representation of the colors distribution in the images (Khokher, A. and Talwar, R., 2012).

Color Moments descritor recover all the images whose color compositions are similar to the compositions color image query. However, they do not capture spatial relationships between areas of the same color, so its power to differentiate between images is limited.

Given an image I, of size $M \times N$, the Color Moments given below

$$\mu = \frac{1}{M*N}\sum_{i=1}^{M}\sum_{j=1}^{N} I_{(i,j)} \tag{1}$$

$$\sigma = \sqrt{\frac{1}{M*N}\sum_{i=1}^{M}\sum_{j=1}^{N}(I_{(i,j)}-\mu)^2} \tag{2}$$

define, respectively, the mean and the standard deviation. Variance is given by σ^2.

2.2 Color Histogram

The color histogram represents the color distribution in the image, its mean represents the number of pixels of each color tone in the image (Lew, M., Sabe, N., Djeraba, C. and Jain, R., 2006).

To extract features based on the color histogram, it is first necessary to quantize the image in a certain amount of color. It is done due the sparseness of the original color histogram itself. For example, in Fig. 2, the RGB color space $(256 \times 256 \times 256)$ was quantized in the RGB color space $(2 \times 2 \times 2)$, thus reducing the number of possible color combinations. After having quantized the image in a number of colors, the histogram is created based on the color of each pixel.

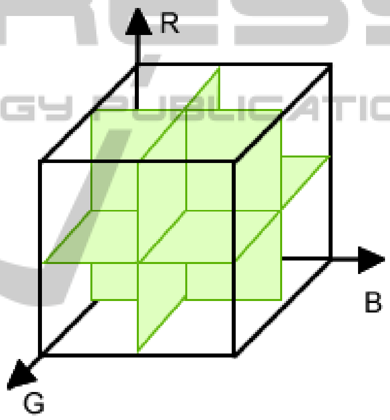

Figure 2: Division of RGB Color Spacer.

2.3 Color Layout Descriptor

Color Layout Descriptor (CLD) is a descriptor designed to capture the spacial distribution of color in an image. The extraction process of features consists in four steps (Manjunath B. S. and Sikora, 2002):

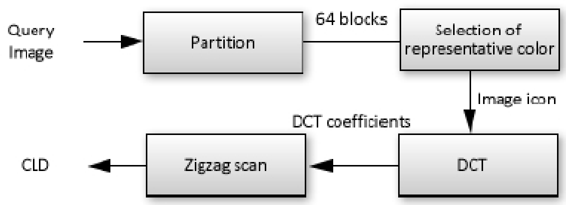

Figure 3: Steps of the Color Layout Descriptor.

1. Image partition: the query image is divided into 64 blocks to assure the invariance of scale and resolution (a).
2. Selection of representative color for each block of

the image: a single color is chosen to represent each block (b).

3. Obtaining coefficients of applying discrete cosine transform (DCT): the image icon is converted from RGB color space to YCbCr color space, then DCT is applied to each band in the image (Y, Cb and Cr) resulting in three dimensional arrays of 64 DCT coefficients.
4. Zigzag Scanning of the found coefficients: is obtained three feature vectors by applying a zigzag scanning on coefficient matrices. The zigzag scanning aims to group elements of low frequency (c).

Figure 4: Steps of the Color Layout Descriptor.

2.4 Co-occurrence

Co-Occurrence Matrix is a two-dimensional matrix, generated from the count of occurrences of spatial patterns in the neighbourhood of a pixel (Jain, R., Kasturi, R. and Schunck, B., 1995) (Sastry, S., Kumari, T., Rao, C., Mallika, K., Lakshminarayana, S. and Ha Sie Tiong, 2012).

For each of the possible combinations between the pixel and the neighboring pixel, is created an element in the co-occurrence matrix, so that the size of co-occurrence matrix is $t \times t$, where t is the number of gray scale present in original image. The illustrates better how is the process of building the co-occurrence matrix.

Note that the value 1 was assigned to the element (1,3) of the co-occurrence matrix. This value is representing the number of occurrences of the combination [1 3] existing in the original image. How this combination [1 3] occurs only once in the image, is stored in the element (1,3) the value 1. As for the element (1,1), was placed the value 2, which symbolizes the existence of two occurrences of the combination [1 1] in the original image.

From the co-occurrence matrix, some interesting characteristics can be obtained. They are: contrast, correlation, energy and homogeneity.

2.5 Entropy of Gray Scale

Entropy represents the dispersion degree of the gray levels of an image and can be used to characterize a texture of image (Jain, R., Kasturi, R. and Schunck, B., 1995).

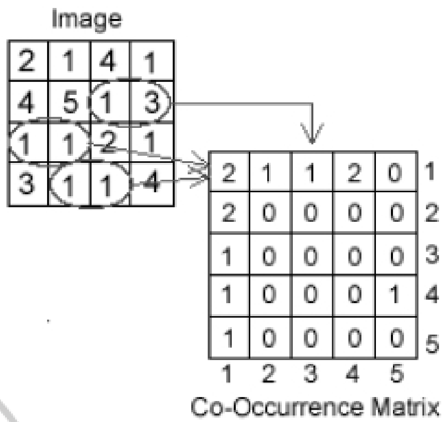

Figure 5: Example of Co-occurrence Matrix.

Given a histogram h of an image I, Entropy can be calculated as:

$$E = \sum_{i=1}^{N} h(i) * \log_2 h(i) \tag{3}$$

2.6 Similarity Measures

Once two feature vectors p and q for the images A and B, respectively, are computed, it becomes necessary to calculate the similarity between these two vectors. Defined as $D(p,q)$ the similarity distance between the features vectors p and q. If D is equal to zero, this means that the two images may be identical and if D is close to zero means that the images are similar.

Some well known equations for calculating the similarity between two vectors are: Euclidean, Manhattan and Minkowski [4, 5 and 6].

$$D(p,q) = \sqrt{\sum_{i=1}^{N} (p(i) - q(i))^2} \tag{4}$$

$$D(p,q) = \sum_{i=1}^{N} |p(i) - q(i)| \tag{5}$$

$$D(p,q) = \left(\sum_{i=1}^{N} |p(i) - q(i)|^r \right)^{1/r} \tag{6}$$

3 THE PROPOSED METHODS

This Section introduces the method to detect phases transitions and the method to detect phases in the analysis of liquid crystal image sequences.

3.1 Phase Transition Detection

The method to detect phase transition receives as input a liquid crystal image sequence and outputs a set of phase transition temperatures. Let n be the number of the images in the image sequence. Each frame of the image sequence is processed by color or texture visual descriptor. For each frame i, it is extracted a feature vector $V_i = \langle v_1, v_2, v_3, \ldots, v_n \rangle$ that represent the frame i. It is done for each frame in order to create an $DV = \langle d_1, d_2, d_3, \ldots, D_n \rangle$ distance vector where, for each i, $d_i = D(V_i, V_{(i-1)})$. The elements of DV may be sequentially considered as values of a one dimensional function. The Fig. 8 to Fig. 12 show the plotting of DV for the same input liquid crystal image sequence computed by several visual descriptors. Peaks and valleys for each plotting represents a possible phase transition. To calculate the values of the peaks and valleys of the found function, just check where the first derivative of the function is equal to zero. Since images contain light interference and may present no uniform results, it was considered an interval Δ_x, where the global maximum (or global minimum) in this interval is taken. It is done in order to avoid to deal with too many roots. Fig. 8 shows the plot obtained by Color Layout Descriptor.

Fig. 6 shows a fluxogram that summarizes the method.

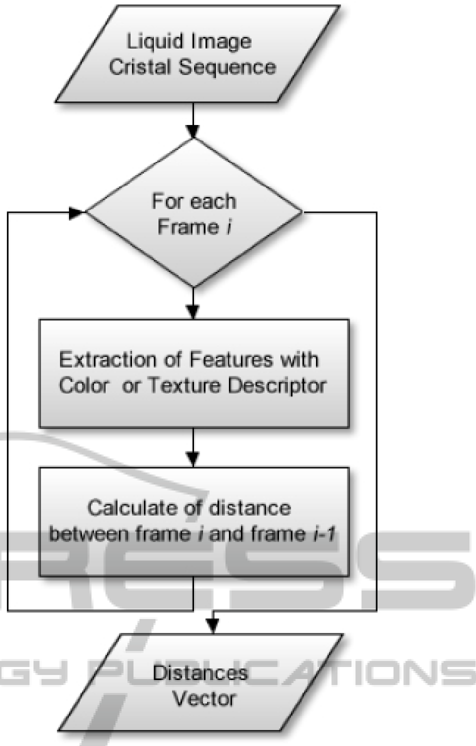

Figure 6: Fluxogram of the method to detect phase transition.

3.2 Phase Retrieval by CBIR

The second method aims to identify the phases of a liquid crystal. This method was based on a CBIR system Fig. 7. It receives as input data a liquid crystal image representing a well defined phase as a searching criterion and also receives an arbitrary liquid crystal image image sequence. The method works as follows:

1. It is created a features vector V_{input} to represent the input image according to a given Visual Descriptor.
2. For each frame i of the input sequence it is computed a features vector V_i.
3. For each vector V_i, it is calculated a similarity measure x_i between it and V_{input}. Such vector is given by $x_i = D(V_{input}, V_i)$.
4. Let $X = \langle x_1, x_2, x_3, \ldots, x_n \rangle$. Let $X_{sort} = \langle s_1, s_2, s_3, \ldots, s_n \rangle$ be a sequence where the elements of X are sorted in a increasing order.
5. If $s_i = x_j$, it means that, among all images from the input image sequence, frame j is the i-th closest frame to the input image criterion. X_{sort} gives the ordering of the frames from input sequence according to their similarity to the input criterion. More, the images from the input sequence which are more probable to belong to the same phase of the input image criterion are related to small s_i, at the beginning of the X_{sort}.

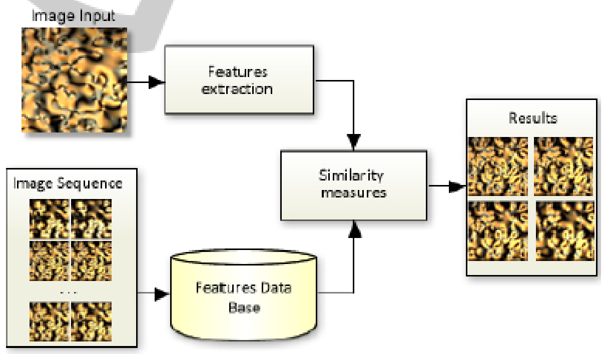

Figure 7: The proposed method to identify the phases of liquid crystal.

4 EXPERIMENTAL RESULTS

The experiments were applied to a known liquid crystal image sequence, acquired from a liquid crystal sample by a well known process (Neto, A.M.F., Liebert, L. and Galerne, Y., 1985) in order to produce some phases. In a previous paper, this liquid crystal sequence showed the following phases (A - B - C - D - A) and was determined, by optical microscopy and optical birefringence measurements, that the temperatures of the phases transitions was: A-B (13.8°C), B-C (18.6°C), C-D (21.2°C) and D-A' (40.3°C).

4.1 Experimental Results to Phase Transition Detection

For the first experiment, the Visual Descriptors were applied to detect the phase transition. The figures 8 to 12 show the plot of the Visual Descriptor result for each image of the sequence. The temperatures where peaks and valleys occurred for each Visual Descriptor are the ones where probably phase transiitions occurs. Table I shows the temperatures of each phase transition found for each visual descriptor. Although somewhat different, all plots in Figures 8 to 12 and data in Table I show correlation to each other.

The descriptor Co-occurrence showed higher accuracy for detecting the A-B phase transition. All color descriptors (Color Layout, Color Moments and Color Histogram) showed the same result for the detection of B-C phase transition, coincides with the real temperature which is 18.6°C. For the detection of the C-D transition the descriptors that showed the best results were the Color Moments and Entropy. In the last phase transition, D-A', the descriptor that found phase transition temperature was of the Entropy. Although they found different temperatures for the transitions, all descriptors found the phase transitions with a small margin of error.

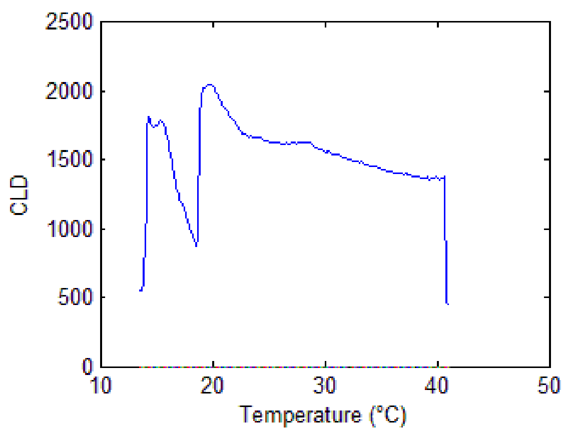

Figure 8: Color Layout Descriptor result.

4.2 Experimental Results to Phase Retrieval

The second experiment was applied to three samples of the liquid crystal sequence. Was chosen an image that belongs to phase B, another image that belongs to phase C and finally one that belongs to phase D.

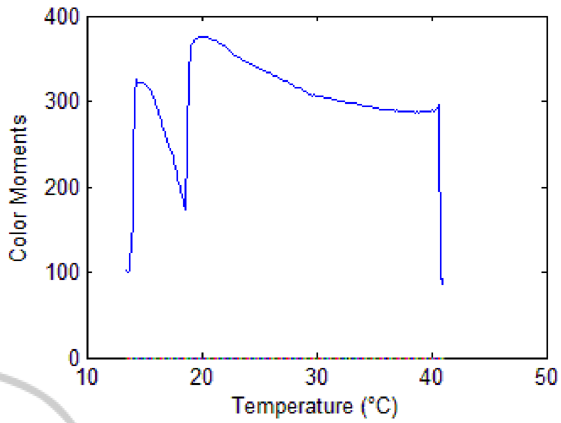

Figure 9: Color Moments result.

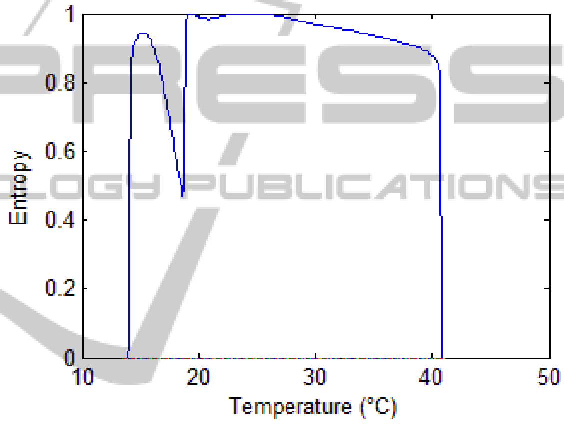

Figure 10: Entropy result.

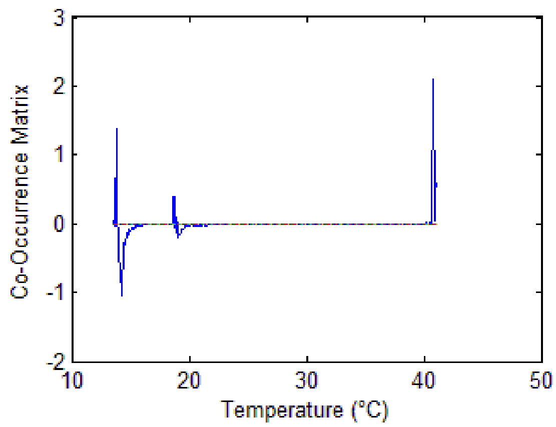

Figure 11: Co-Occurrence result.

In the experiment of the first sample, the selected image is in the temperature of 15.0C°C , it has 49 relevant images that are between 13.8°C and 18.6°C. In the second sample, the selected image is in the temperature of 19.5°C and it has 36 relevant images that are between the temperatures of 18.5°C and 21.2°C. In the last sample, the selected image is in the temperature of 30.0°C and it has 185 relevant images that are between the temperatures of 21.2°C and 40.3°C. One way to rank the visual descriptors is using the functions of $Precision$ and $Recall$. To calculate the Precision, is necessary to consider the value n which means how many images must be retrieved from the database. The results of the experiments are shown in Tables II, III and IV.

$$Precision = \frac{\#(retrieved\ relevant\ images)}{\#(retrieved\ images)} \quad (7)$$

$$Recall = \frac{\#(retrieved\ relevant\ images)}{\#(relevant\ images\ in\ collection)} \quad (8)$$

5 CONCLUSIONS

This paper introduces two methods for liquid crystal image sequences processing. One of them is applied to detect phase transitions in such sequences and the other one classifies the phases based on a input image which criterion is defined by its known phase, ordering frames according to the similarity to the input criterion.

Both methods use Visual Descriptors. Color and texture descriptors showed to be very efficient to extract information from the complex structures, in order to make easier the proposed tasks.

For the method to detect phase transition, all the descriptors exhibited good results. The experiments showed that all visual descriptors found the phase transitions with high accuracy, since they found transition temperature values close to the real measured ones. Colors descriptor had better precision to some phases transition and texture descriptor were better for others. For phase transition D-A', the texture descriptors found values closer to the real value. The phase transition B-C was best identified by color descriptors. For the other transitions, all visual descriptors presented very approximate answer to real value.

In the experiment for phase retrieval the color descriptors showed better results. For n equals to 10, color descriptors classify all phases with 100% of *Precision*. The calculation of *Recall* function showed that is recovered at least 59% of all relevant images when the color descriptor is used. Texture descriptors didn't show good results as the color descriptors, with exception to identification of the phase D.

In a future work, it is possible to combine the two methods presented in this paper for best results. Once discovered phase transitions and how many phases a liquid crystal possesses, is possible, from a database of known liquid crystal image sequences, to classify these phases and the temperature of each found phase transition.

REFERENCES

Bahadur, B. (1992). *Liquid Crystals - Applications and uses*. World Scientific Pub Co Inc.

Cess, G., Snoek, M. and Worring, M. (2005). Multimodal video indexing: A review of the state-of-the-art. *Multimedia Tools and Applications*, 25:5–35.

Jain, R., Kasturi, R. and Schunck, B. (1995). *Machine Vision*, chapter 7. McGraw-Hill.

Khokher, A. and Talwar, R. (2012). Content-based image retrieval: Feature extraction techniques and application. *International Journal of Computer Applications*, pages 356–361.

Lew, M., Sabe, N., Djeraba, C. and Jain, R. (2006). Content-based multimedia information retrieval: State of the art and challenges. *ACM Transactions on Multimedia Computing, Communications, and Applications*.

Manjunath B. S., Salembier, P. and Sikora, T. (2002). *Introduction to MPEG-7*. John Wiley and Sons.

Montrucchio, B., S. A. and Strigazzi, A. (1998). A new image processing method for enhancing the detection sensitivity of smooth transitions in liquid crystals. *Liquid Crystals*, 24(6):841–852.

Sampaio, A., P. A. and C., V. (2004). Investigation of uniaxial and biaxial lyotropic nematic phase transitions by means of digital image processing. *Molecular Crystals and Liquid Crystals*, 408(1):45–51.

Sastry, S., Kumari, T., Rao, C., Mallika, K., Lakshminarayana, S. and Ha Sie Tiong (2012). Transition temperatures of thermotropic liquid crystals fromthe local binary gray level cooccurrencematrix. *Hindawi Publishing Corporation*, 24:9.

Snoek, C. and Worring, M. (2005). Multimodal video indexing: A review of the state-of-the-art. *Multimedia Tools and Application*, 25:5–35.

APPENDIX

Table 1: Experiment with the sample temperature 15.0 °C.

Descriptor	Precision (n=10)	Precision (n=20)	Recall
Color Layout	100%	100%	66.7%
Color Moments	100%	100%	63.9%
Entropy	30%	40%	61.1%
Co-occurrence	70%	70%	72.2%
Color Histogram	100%	100%	63.9%

Table 2: Experiment with the sample temperature 19.5 °C.

Descriptor	Precision (n=10)	Precision (n=30)	Recall
Color Layout	100%	80%	99.5%
Color Moments	100%	66.7%	96.8%
Entropy	50%	30%	82.2%
Co-occurrence	32%	30%	26.7%
Color Histogram	100%	66.7%	59.2%

Table 3: Experiment with the sample temperature 30.0 °C.

Descriptor	Precision (n=10)	Precision (n=100)	Recall
Color Layout	100%	100%	99.6%
Color Moments	100%	100%	96.8%
Entropy	100%	95%	82.2%
Co-occurrence	100%	96%	88.1%
Color Histogram	100%	100%	91.9%