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To cite this article: Hélio Siebra et al 2015 J. Phys.: Conf. Ser. 574 012116

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Fuzzy Clustering of Color Textures using Skew Divergence and Compact Histograms: Segmenting Thin Rock Sections

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Abstract. Digital image segmentation is the process of assigning distinct labels to different objects in a digital image, and clustering techniques can be used to achieve such segmentations. However, many traditional segmentation algorithm fail to segment objects that are characterized by textures whose patterns cannot be successfully described by simple statistics computed over a very restricted area. In this paper we present a fuzzy clustering algorithm that achieves the segmentation of images with color textures by employing a distance function based on the Skew Divergence, that is based on the well-known Kullback-Leibler Divergence. In order for such a distance to produce good results when applied to color images, we reduced the dimensionality of the image’s histogram, thus eliminating the sparsity of the color histogram and speeding up the execution of the algorithm. We performed experiments on thin rock sections and compared our results to the segmentations obtained by the Fuzzy C-Means and by another fuzzy segmentation technique, showing the superiority of our approach.

1. Introduction

Digital image segmentation is the process of assigning distinct labels to different objects in a digital image, i.e., the task of finding which pixels belong together. However, the level of detail indicated by the labeling depends on the application at hand. To perform object identification on digital or continuous images humans make use of high-level reasoning and knowledge, as well as of several visual hints. This task becomes particularly hard for a computer program when the images is affected by noise and/or inhomogeneous illumination or when the objects in the images are distinguished not by intensity itself, but by textural properties.

As mentioned by Forsyth and Ponce [1], textures are everywhere, easy for a human to recognize, but hard to define them precisely. Usually, textures are described as the feel or shape of a surface or substance, and in the areas of imaging they are characterized by statistical distributions of the observed intensities. Textures can be classified as structural or non-structural [2], where structural textures have a repeated pattern associated with a texture periodicity [3], and non-structural or statistical textures do not possess this characteristic and are globally or locally described by statistical distributions. Since visual textures can perceived as such depending on the observation scale, these distributions can change according to it.

1 We would like to thank the support of the grant FAPERN PRONEM No 610006/2010.
The ubiquity of textures in nature makes the capacity of their segmentation in images a very important one. Visual problems in which the segmentation, description and identification of objects with textural properties in digital images or videos permeate several application areas such as Medicine, Security, Agriculture and Biology. In this work, we choose a problem in the field of Geology, the segmentation of thin rock samples, to show the applicability and efficiency of the proposed method.

The rest of this work is organized as follows. Section 2 briefly describes related techniques that can be used to segment objects with textural properties in monochromatic and color images, while Section 3 talks about the proposed method by describing the distance function used in the clustering process, as well as the procedure used for reducing the histogram dimensionality. Section 4 presents and discusses the experimental results, while Section 5 highlights the contributions and outlines possible future works.

2. Segmentation and Clustering of Textures

In this work, we are concerned with the segmentation of images that contain objects which are characterized by statistical textures, a much harder problem than when dealing with structural textures. Several different techniques have been employed to perform texture segmentation. One example of these techniques is the one proposed by Unser and Eden [4], where they extract local texture properties using local linear transforms that were optimized for maximal texture discrimination. Then, they reduce the texture features to a single component that is then thresholded to produce the segmentation. A very different approach is proposed by Hofmann et al. [5] that also performs unsupervised texture segmentation, but does it by relying on statistical tests as a measure of homogeneity. The texture segmentation task is then formulated as a clustering problem and solved by computing dissimilarities using multi-scale Gabor filters.

There are several model-based approaches [6, 7] that attack the texture segmentation problem by modeling the intensity field of textures as a Gauss-Markov or as a Markov random field to represent the local spatial dependencies between pixel intensities. However, these techniques are usually very computationally intensive because they require a large number of iterations to converge. These techniques would become even more computationally demanding if they were applied to the segmentation of color images.

There are also approaches based on fuzzy segmentation algorithms, such as the Fast-MOFS, proposed in [8]. The main advantage of this class of algorithm is its flexibility, since it can be easily adapted to work with different grids [9], or to incorporate color information in the computation of grades of membership [10]. This method has been successfully used in the segmentation of images acquired using varied modalities, such as MRI [8], CT [8] and EM [11].

The Fast-MOFS algorithm was later refined into the FAST-MOFS2 [12], providing for a simpler and more efficient implementation. However, the fuzzy affinity functions employed lacked the ability of gathering enough information for proper texture characterization. In order to cope with that, we introduced the concept of adaptive affinity functions [13], that allowed the algorithm to decide, at running time, on the appropriate size of the neighborhoods used. Even with the increased capacity for segmenting textures, this method still has problems when applied to images which contain objects that are characterized by more complex textures or that are formed by several isolated groups of pixels.

Here we analyze the behavior of three fuzzy clustering methods for segmenting color images. The first one is the conventional FCM (Fuzzy C-Means). As mentioned by [14], since the FCM does not consider any spatial information in the image context, it usually is very sensitive to artifacts such as noise or non-uniform illumination.

The second method is the one proposed by Samet et al. [15], that works by selecting a region which contains the mineral that is to be segmented in the rock thin section. Then, the RGB channels of these samples are median filtered and the three resulting histograms are used
as membership functions. These membership functions are used to calculate the membership values of all pixels to the mineral from which the sample was taken. Pixels whose associated RGB values satisfy an user-defined fuzzy rule are considered to have strong membership to the mineral object. These pixels plus the pixels deemed to have weak membership to the mineral object, but that are connected to a pixel with strong membership, become part of the mineral object. Another samples can then be used to improve the quality of the segmentation.

The third one is a clustering algorithm that employs fuzzy affinity functions used with the FAST-MOFS2 [12] family of algorithms. These fuzzy affinity functions use the Skew divergence to compute the distance between the distributions of gray levels surrounding two pixels.

### 3. Skew Divergence of Color Histograms

Since we are interested in the characterization and further segmentation of objects which possess textural properties, specifically non-structural or statistical textures, it is that. In the fields of Statistics and Information Theory, the very well-known Kullback-Leibler (KL) divergence [16], also known as relative entropy is a non-symmetric measure of the distance or difference between two probability distributions $q$ and $r$. Specifically, in Information Theory, the KL divergence of $r$ from $q$, denoted by $KLD(q||r)$, is a measure of the information lost when $r$ is used to approximate $q$, and is given by

$$KLD(q||r) = \sum_y q(y)(\log q(y) - \log r(y)).$$

(1)

The KL divergence is widely used to measure how far away are two distributions. However, the KL divergence is not defined when $r(y) = 0$, and that happens quite often when we are dealing with distributions that are characterized by histograms with few counts. For example, if we are dealing with monochromatic images with 256 gray levels and neighborhoods of size $9 \times 9$, we are characterizing a distribution by using a histogram with 256 bins and whose total count is 81.

In order to deal with this problem, Lee [17] proposed an asymmetric divergence, the Skew divergence, that can be seen as an approximation of the KL divergence and is given by

$$SD_\alpha(q, r) = D(r||\alpha q + (1 - \alpha) r),$$

(2)

for $0 \leq \alpha \leq 1$, where $\alpha$ can be seen as a degree of confidence in the distribution $q$ and $(1 - \alpha)$ as the amount of smoothing of the distribution $q$ over $r$. This allows us to work nicely with sparse data problems, such as the low count histograms of small neighborhoods.

This problem is amplified when we work with color images. If we are working with a color image where the intensity of each channel is represented by a byte, then we would be dealing with histograms with $256^3$ bins or possible colors. This implies that we would be dealing with very sparse data, aside from the fact that the computation time of the KL or Skew divergences would be much larger than in the monochromatic case.

A solution to this problem is to perform a requantization, using a smaller number of bits to represent each channel. Usually, if this reduction is not very large, a very similar color image is produced. Similarly to what was performed in [18], we perform a further reduction of the dimension of the histogram by discarding colors whose bins have smaller counts than a specified value $c$. The counts associated with the discarded colors are associated to the closest color that was not discarded. Since we have to group colors that are perceptually similar, i.e., look closer for a human observer, we used the CIELAB color space, that is more perceptually uniform than the RGB color space.

Our method performs the clustering of color images which contain textural objects by computing the Skew divergence between the distributions of neighborhoods surrounding seed
pixels and the other pixels. For a particular pixel $p$, we compute the Skew divergence between it and all seed pixels of all objects. After this, the smallest divergence value indicates the winner seed pixel, which will indicate the object to which the pixel $p$ will be associated. These divergence values are normalized to the range $[0, 1]$, with 1 indicating that the pixel $p$ has an identical distribution to a particular seed pixel. This divergence value can be seen as the fuzzy grade of membership of $p$ to the object to which it belongs.

4. Experiments and Discussion

In order to show the applicability of the method proposed in this work, we choose to use it to segment images of thin sections of rock. Thin rock sections are produced from small slabs of rock that are glued with epoxy to a glass slide and ground down until they reach the appropriate thickness (approximately $30 \mu m$ thick). Usually, this grinding method involves using an interference color chart and a mineral color as a gauge to infer the thickness of the section. Typically quartz is used since it is one of the most abundant minerals.

These thin sections are then viewed using an optical microscope and are mainly used to investigate the optical properties of the minerals present in the sample. This is a common task in the field of petrology that is used to gather information about the origin and evolution of the parent rock or about the geometrical arrangement of the different minerals present in the sample. Usually, the segmentation of rock thin section images is not a trivial task due to the intricate patterns that the minerals can be arranged in the samples.

Here, we show the segmentations of two thin rock sections, one with $607 \times 354$ (Figure 1a) and the other with $607 \times 486$ (Figure 1f). The images were segmented manually with the aid of an image processing interface to produce the ground truth segmentations shown in Figures 1b and 1g. The experiments were run on a computer with an Intel Core 2 Duo E7400 running at 2.80GHz and 4Gb of RAM memory.

Based on experiments performed with different images, we requantized each color channel selected, so that each color channel is represented by 3 bits, i.e., 8 different intensities per channel. Then, every color whose associated histogram bin had less counts than 0.1% of the number of pixels of the image was associated to the closest color according to the distance between colors computed in the CIELAB color space. This color space reduction is performed prior to the seed pixel selection, so, once it is done, the Skew divergence computation is performed as it was done in a monochromatic image.

The neighborhood size used was 9, i.e., each histogram used for computing the Skew divergence contains a total of 81 counts. Once the histograms of two neighborhoods are available, they are used to compute the Skew divergence, by using $\alpha = 0.67$. In both cases, the total number of bins of the histograms was smaller than 100, and so, the Skew divergence computation was faster than if we were dealing with complete histograms on monochromatic images. The running times for the clustering of images 1a and 1f were approximately 3.3s and 4.3s, respectively.

The specific accuracy values of the segmentations for Figures 1a and 1b were 66.31% (Fuzzy C-Means), 78.65% (Samet et al. [15]) and 94.22% (proposed method), and 70.69% (Fuzzy C-Means), 87.72% (Samet et al. [15]) and 95.59% (proposed method). We can see from these results that the proposed method is clearly superior to the other two tested methods. We can also see in Figures 1d and 1i that the segmentations produced by the method of Samet et al. [15] does not label all pixels. This happens because the fuzzy membership values computed for all objects are smaller than the threshold used by the method. We can also see that the Fuzzy C-Means results are noisier than the other two and misclassify several regions of the two images.

On the other hand, while the proposed method produces the most accurate segmentation in both examples, it tends to overlook small areas originally classified as an object. That happens when there are objects with parts that are thinner than the support of the filter used as a neighborhood for computing the Skew Divergence.
Figure 1. Original images of the rock samples (a and f) and its segmentation ground truth (b and g). Segmentations produced by using FCM (c and h), Samet et al. method (d and i) and the proposed method (e and j).

5. Conclusion
In this work we proposed a new fuzzy clustering method for segmenting color images that have objects which are characterized by textural properties. The method works by reducing the dimensionality of color histograms through requantization of the RGB color channels followed by the elimination of colors that do not appear often in the image. This reduction allows us to use the Skew divergence to calculate the distance between the distributions of two pixels’ neighborhoods.

The efficacy of the proposed method was tested in the application of segmenting thin rock samples. The results show that our method is more accurate than the traditional Fuzzy C-Means and another fuzzy clustering method [15].

Future work will include the usage of the method proposed here to other applications, such as the segmentation of dermoscopic lesions or natural images. We also plan to analyze the robustness of this method when applied to noisy data and the automation of the segmentation for specific applications.

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