

# A ROBUST ALGORITHM FOR BINARIZATION OF OBJECTS

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**Abstract**— Many times, binarization is recognized to be one of the most important steps in most high-level image analysis systems; particularly, for the object recognition. However, experience has shown that the most effective methods continue to be the iterative ones. In this work, entropy is used as a stopping criterion when segmenting an image by recursively applying mean shift filtering. Of this way, a new algorithm for the binarization of objects is introduced.

**Keywords**— Images segmentation, mean shift, algorithm, binarization, entropy, Otsu's method.

## I. INTRODUCTION

Many binarization methods have been proposed; particularly, for medical-image data (Kenong *et al.*, 1995; Sijbers *et al.*, 1997; Chin-Hsing *et al.*, 1998; Shareef *et al.*, 1999; Schmid, 1999; Koss *et al.*, 1999). Unfortunately, binarization using traditional low-level image processing techniques, such as thresholding, region growing and other classical operations require a considerable amount of interactive guidance in order to attain satisfactory results. Automating these model-free approaches is difficult because of complexity, shadows, and variability within and across individual objects.

Today, the most robust segmentation algorithms are the iterative methods, which cover a variety of techniques; for example, mathematical morphology, deformable models, thresholding methods and others. However, one of the problems of these iterative techniques is the stopping criterion, where many methods have been proposed (Chenyang *et al.*, 2000; Vicent and Soille, 1991; Cheriet *et al.*, 1998)

Mean shift is a non-parametric and versatile tool for feature analysis and can provide reliable solutions for many vision tasks (Comaniciu, 2000; Comaniciu *et al.*, 2002). The mean shift was proposed in Fukunaga and Hostetler (1975) and largely forgotten until Cheng's paper (Cheng, 1995) retook interest on it. Segmentation by means of the mean shift method carries out as a first step a smoothing filter before segmentation is performed (Comaniciu, 2000).

The term of entropy is not a new concept in the field of information theory. Entropy has been used in image restoration, edge detection and recently as an objective evaluation method for image segmentation (Zhang *et al.*, 2003).

In this work a new binarization strategy based on the computation of the mean shift is proposed. The proposal

makes use of entropy as a stopping criterion, where the binarization is carried out after the segmented image is obtained.

The obtained results with this algorithm are compared with other developed by the author and collaborators and also, with the Otsu's method (Rodríguez *et al.*, 2005; Rodríguez *et al.*, 2002a; Rodríguez *et al.*, 2003). In other words, our interest in this research is to determine which algorithm is the most suitable and robust for object binarization; in this case, blood vessels. In this work the important information to be extracted from images is just the number of objects.

The remainder of the paper is organized as follows: In Section 2, we provide the more significant theoretical aspects of the mean shift. In Section 3, we shortly introduce the entropy concept. In Section 4, we describe our binarization algorithm based on the mean shift by taking entropy as a stopping criterion. In Section 5, the experimental results, comparisons and discussion are presented. In this section a quantitative verification of the obtained results is also carried out. Finally, in Section 6 the conclusions are exposed.

## II. THEORETICAL ASPECTS

The iterative procedure to compute the mean shift is introduced as normalized density estimate of the gradient. By employing a differentiable kernel, an estimate of the density gradient can be defined as the gradient of the kernel density estimate; that is,

$$\hat{\nabla}f(x) = \nabla\hat{f}(x) = \frac{1}{nh^d} \sum_{i=1}^n \nabla K\left(\frac{x-x_i}{h}\right) \quad (1)$$

where  $n$  is the data points.

The kernel function  $K(x)$  is now a function, defined for  $d$ -dimensional  $x$ , satisfying

$$\int_{R^d} K(x)dx = 1 \quad (2)$$

Other conditions on the kernel  $K(x)$  and the window radio  $h$  are derived in order to guarantee asymptotic unbiasedness, mean-square consistency, and uniform consistency of the estimate in the Eq. (1) (Fukunaga and Hostetler, 1975). For example, for *Epanechnikov* kernel:

$$K_E(x) = \begin{cases} 1/2 c_d^{-1} (d+2) (1-\|x\|^2) & \text{if } \|x\| < 1 \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

$$\hat{\nabla}f_E(x) = \frac{1}{n(h^d c_d)} \cdot \frac{d+2}{h^2} \sum_{x_i \in S_h(x)} (x_i - x) = \quad (4)$$