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Entropic image segmentation of sessile drops over patterned acetate

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Abstract

An entropic segmentation method is presented and applied to the contour detection of water drops over patterned surfaces. Jensen–Shannon divergence is computed from a double sliding window in the image to get a real number matrix, in which a region growing procedure is performed in a similar way to usual watershed. Then a region merging process is achieved, and the optimal configuration is selected to obtain the complete drop contour. Once the drop contour is detected from top-view images, the contact angle might be readily computed from the area enclosed by the contour and the drop volume.

From the results obtained the proposed method outperforms other usual methods, like watershed or Canny.

Keywords: Image segmentation; Jensen–Shannon divergence; Region growing and merging; Sessile drop; Contour detection

1. Introduction

Contour extraction of drop images is a task of major interest for determining contact angle, having many practical applications [21,22,26]. Although very different methodologies have been proposed to solve the drop contour detection problem [13], none of them is: robust under noise and background patterns, flexible enough to be applicable in all the cases and unsupervised. Edge-detection based techniques have the drawback to usually lead to fragmented edges. Variational approaches such as active contour [6,7] are suitable techniques, but they have the drawback of requiring an initial curve that, in the presence of disturbing elements (such as noise, textures, lighting defects, and reflections), must be very close to the boundary to achieve a reliable result. Other typical approaches are based on structural and decision theoretic methods, such as minimum distance, Bayesian, neural networks and expected maximization algorithms. Statistical methods such as Markov Random Fields [28,19] are usually based on the assumption of a known analytic expression for the distribution functions of the pattern classes, but this may be unrealistic.

Wetting phenomena are always ruled by contact line interactions, as predicted by the local Young equation, rather than by the wetted area energy. However, it is a non-trivial task to measure the local contact angles of distorted sessile

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drops (with corrugated contact line). In these cases, the effective contact angle averaged over the wetted area becomes more helpful. ADSA-D [25,1,14,15] enables to overcome these shortcomings. Instead of side-view images, top-view drop images are captured. For contact angles smaller than 90° the contact line is visible and a set of contact point co-ordinates are obtained from it to calculate the average contact diameter. For contact angles greater than 90° the drop equator is visible, and a set of extracted point co-ordinates yields the maximum diameter. Frequently, the image processing fails due to the lack of optimal contrast for thresholding the drop image from a heterogeneous background. In these cases, an incomplete contour is usually extracted. Once the drop diamater is obtained, the fit process is fully automated. The ADSA-D algorithm uses the drop volume as a parameter in the contact angle calculation. For this reason, the drop volume must be known with accuracy.

The drop/bubble and meniscus profile detection from side-view images is fully automated using local gradient operators. But for top-view drop images, a complete automation of contact line detection, applicable to diverse liquids and substrate surfaces is a very complex task, due to low contrast and different image textures. To our knowledge, there are few proposal of semi/full-automated contact line detection reported in literature.

Many image segmentation algorithms use the main idea that (1) every region should be internally homogeneous in some sense, while (2) every two adjacent regions must have different features (while remaining each one internally homogeneous). However, usually it is difficult to select the optimal set of regions that fulfil the two above conditions and yields drop contour. Thus, these methods typically fail to merge the regions that must be separated, or fail to split the regions that must not be separated, because the information about the uniformity of a region and the heterogeneity between different regions is difficult to be incorporated into the algorithms.

Here, we propose a global segmentation technique based on a region growing and merging approach. It uses the Jensen–Shannon divergence (*JS* hereinafter) to measure uniformity inside the same region and heterogeneity between different regions. This entropic measure has been used successfully in edge detection algorithms [3,11,2]. The proposed segmentation method consists of three steps: (1) calculation of *JS* for every image pixel (the *JS* matrix); (2) region growing of the *JS* matrix, obtaining an over-segmented image; (3) region merging of the over-segmented image.

2. Image segmentation by entropic region growing and merging

The proposed segmentation method is based on the Jensen–Shannon divergence (*JS*). Proposed by Lin [17], *JS* is an Information Theory measure of inverse cohesion between probability distributions. Given two probability distributions P_1 and P_2, taken from the same probabilistic space, *JS* is defined as:

$$JS(P_1, P_2) = H\left(\frac{P_1 + P_2}{2}\right) - \frac{H(P_1) + H(P_2)}{2} \tag{1}$$

where $P_k = \{p_{k1}, p_{k2}, \ldots, p_{kn}\},\ k = 1, 2$ are two probability distributions, and

$$H(P_k) = H(\{p_{k1}, p_{k2}, \ldots, p_{kn}\}) = -\sum_{i=1}^{n} p_{ki} \log_2 p_{ki} \tag{2}$$

is the well-known Shannon's entropy of P_k.

Mathematical properties of *JS* and advantages of using it for segmentation applications are described in the literature [11,12,23]. Among the most relevant we can mention: it is nonnegative, bounded and symmetric with respect to its arguments; it can be generalized to any number of distributions greater than two, and its square root is a metric [10,18]. Another interesting property of *JS* is that the distributions can be weighted. This fact has been used with advantage in symbolic sequence segmentation by taking the weights according with the nature of the data [20,4].

2.1. The segmentation procedure

The segmentation procedure follows the well-known watershed scheme [27] and works in three steps.

- *JS* matrix calculation: a divergences matrix is obtained from the image. In this step, every pixel in the original image is labelled with its *JS* value, the likelihood of being a boundary pixel located between different regions. This matrix of real numbers is scaled in [0, 1].