Matlab Graphic User Interface for image segmentation using Markov random fields and entropy estimation with parallel processing.

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***Abstract*—In this work it is presented, described and tested a new Matlab Graphic User Interface (GUI) for image segmentation of degraded images using two probabilistic techniques, Markov random fields (MRF) and nonparametric entropy estimation. This GUI was created in order to integrate a series of steps needed for the segmentation process into a single visual environment to allow an easier handling of input images and saving of results. It is also used a powerful utility of the Matlab software concerning to parallel processing, with the aim of reduce the computational time because of the high time consumption of this kind of algorithms. Results show a very satisfactory performance of this tool, allowing us to make this task easier and faster.**

Keywords — image segmentation; Markov random fields; entropy estimation; graphic user interface; parallel processing.

I. INTRODUCTION

Segmentation of degraded images is a problem that has been widely studied, and a very useful approach that have helped significantly to solve it, is the use of Markov Random Fields (MRF) within a Bayesian framework [1-8], since MRFs allow to pose this kind of problems as statistical estimation problems where the solution is going to be estimated from a degraded image, that is, the observed data. The basic idea of these methods is to construct a Maximum A Posteriori (MAP) estimate of the probability density function (pdf) corresponding to the image model in order to find the maximum of such distribution, which provides the estimated image closest to the real one.

The classic MAP estimator is defined by:

$$\begin{aligned} \hat{x}_{\mathrm{MAP}} &= \operatorname*{argmax}_{x\in\mathbb{X}}\{p(x|y)\} \\ &= \operatorname*{argmax}_{x\in\mathbb{X}}\{\log p(y|x) + \log g(x)\} \\ &= \operatorname*{argmin}_{x\in\mathbb{X}}\{-\log p(y|x) - \log g(x)\}, \end{aligned} \tag{1}$$

where $g(x)$ is a MRF function that models the prior information of the phenomena to be estimated as a probability distribution, $\mathbb{X}$ is the set of image elements capable to maximize $p(x|y)$ and $p(y|x)$ is the likelihood function from y given x [9].

In [10] it was introduced a new proposal of MRF for image segmentation, called semi-Huber potential function. In this paper it was addressed the problem of segmenting images degraded with Gaussian noise. Some other MRF models reported in the literature (Generalized Gaussian MRF [4], Welsh and Tukey potential functions [11,12]) were taken as a reference in order to prove the results obtained with that new proposal, finding that they were consistent with respect to those obtained with the other models, standing out the advantage that the proposed model contains a lower number of parameters to be tuned to obtain the desired segmentation according with the image type to be processed.

Nevertheless, in some applications the noise is nonGaussian or unknown, and with this previous approach the model is not able to identify the nature of the degradation factor, thus the results are not good. In that sense, in [13-16] a new approach was introduced to deal with other kinds of noise. In [10], the first term in the MAP estimator was defined as a quadratic function of the differences between real and observed data, because the noise considered was Gaussian. But in this new context (nonGaussian), it is assumed a limited knowledge about the noise pdf, $p(e) = p(y|x)$, and the likelihood term is estimated starting with the data itself by means of a nonparametric entropy estimate, resulting in the new MAP Entropy Estimator (MAPEE).

The general form of this new estimator is presented here for quick reference:

$$\hat{x}_{\mathrm{MAPEE}} = \arg\min_{x\in\mathbb{X}}\left\{\mathrm{H}_A\left(\hat{p}_{n,h}(e_E)\right) - \log g(x)\right\}, \tag{2}$$