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Iterated random walks with shape prior☆

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ABSTRACT

We propose a new framework for image segmentation using random walks where a distance shape prior is combined with a region term. The shape prior is weighted by a confidence map to reduce the influence of the prior in high gradient areas and the region term is computed with k-means to estimate the parametric probability density function. Then, random walks is performed iteratively aligning the prior with the current segmentation in every iteration. We tested the proposed approach with natural and medical images and compared it with the latest techniques with random walks and shape priors. The experiments suggest that this method gives promising results for medical and natural images.

1. Introduction

Image segmentation has an important and fundamental role in computer vision. The purpose of image segmentation is to localize objects or regions of interest in a certain image. Segmentation is still very challenging because it must deal with several issues such as occlusion, weak edges or lack of contrast of the object to segment. In order to solve these issues, many methods have been implemented but the problem is still open.

In this work, we focus on the random walks algorithm. Random walks based image segmentation is a graph-based segmentation method proposed by Leo Grady [1] in 2006. This technique has become very popular because it can deal with weak boundaries efficiently, and the extension to 3D and the multi-label segmentation is straightforward [1]. According to the author, random walks can outperform the well-known graph cuts [2] in terms of weak boundaries, since the latter is more susceptible to the "small cuts" problem in the presence of weak boundaries [1]. Moreover, random walks do not require any complex technique to be extended to multi-label segmentation unlike graph cuts which usually use sophisticated alpha-beta methods [3].

Generally, images are not separable via intensity information. Thus, a shape prior may be incorporated in order to separate the object of interest from the image. There are some techniques to incorporate prior knowledge into random walks. For example, a pedestrian segmentation method is developed using random walks with a shape prior in Ref. [4]. A pedestrian shape prior model is built averaging the training data for every pose, as well as averaging all training data to obtain a general prior model. The resulting shape models are integrated into the random walks formulation. The modified random walks is applied for every shape model separately, and the final segmentation is the one with higher probability. A similar work was proposed by Baudin et al. in Ref. [5] applied to the skeletal muscle. The prior term is derived from learning a Gaussian model based on previous segmentations of the thigh muscles in a training set. The segmentations in both works may fail when the average model is too different from the target image or the registration is not very accurate. The same issues may occur in Ref. [6] where the algorithm relies on a probabilistic atlas as a prior knowledge. Therefore, Baudin et al. proposed a new technique to handle large scale deformations by allowing the model to evolve in a low-dimensional shape space of valid segmentations. The authors extended the random walks algorithm introducing principal components into the formulation in which shape deformation is constrained to remain close to PCA shape space built from training examples [7]. However, the method only yields an approximate solution and PCA can neither deal properly with probabilities nor allow representing shapes

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0262-8856/

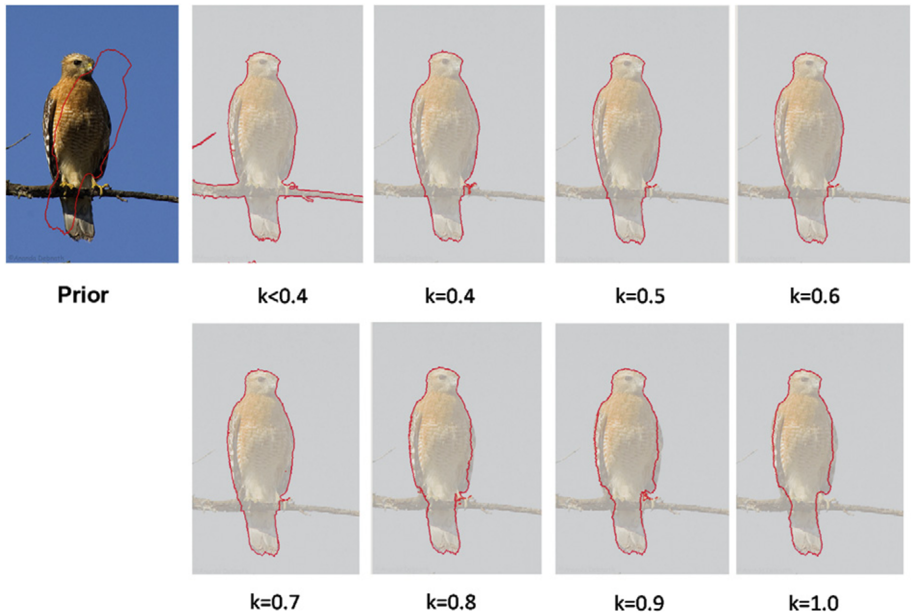

Fig. 1. Influence of the confidence map with varying k.

which differ too much from standard shapes [8]. Therefore, they suggest as a future direction to find a different shape space more compatible with probabilities such as a barycentric model. A similar work using PCA is presented in Ref. [9] but it is also very sensitive to the average shape. In order not to be constrained to the average shape, the guided random walks were proposed [10] where the closest subject in a given database is retrieved to guide the segmentation. If there is no matching case in the database to guide the segmentation, the conventional random walks algorithm is performed. The guided random walks method is applied to the target image guided by every sample in the training dataset. It returns the segmentation with the highest overlap between the segmentation result and the manually segmented training sample, or it performs the conventional random walks if there is not enough overlap in the training set. The limitations of this method are that all the samples of the training data must be considered and if there is not a good match, it only relies on the conventional random walks. Random walks with shape prior have also been used in video tracking and segmentation [11,12]. In Ref. [11], a human segmentation method from a video is implemented in which a model of the human shape is used as a prior and the segmentation likelihood is propagated. In Ref. [12], the segmentation result is also propagated as a prior mask and a spatial cue, obtained from the prior, and a colour cue are fused using Bayesian inference. A disadvantage of these tracking methods is that they can propagate errors.

Besides incorporating the prior, Leo Grady also extended the method to include unary node information as the data term of graph cuts and added a non-parametric probability density model

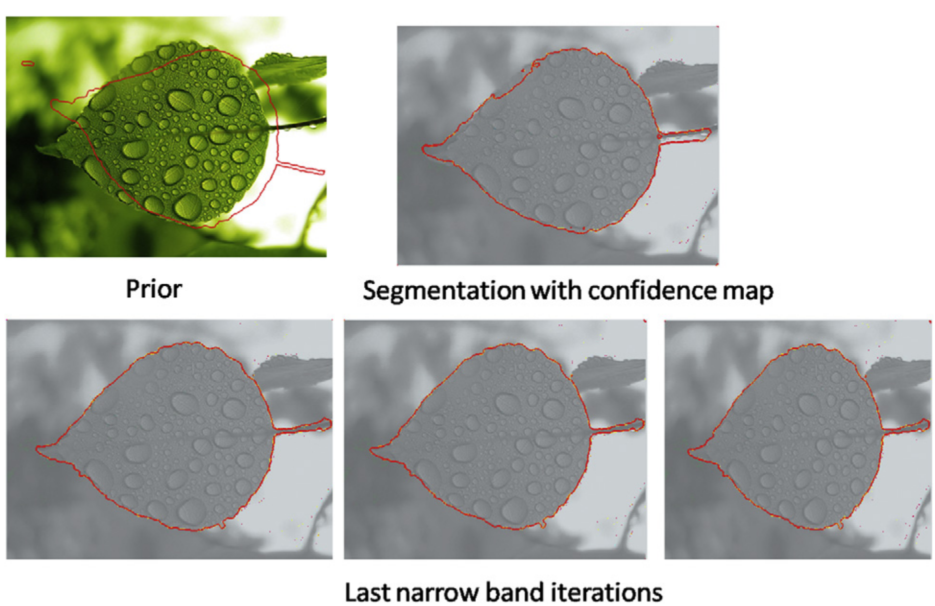

Fig. 2. Example of refinement steps for an image. Top row: shape prior (left) and segmented image using the confidence map (right). Bottom row: different iterations of the refinement step.