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A Semi-Supervised Automatic Optimization Model for Segmentation of Multiple Images

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Abstract

A semi-supervised optimization model for determining an efficient segmentation of many input images is proposed. The advantage of optimization model is twofold. Firstly, the segmentation is highly controllable as the portion chosen for segmentation can be specified by providing the labeled pixels in images for the model either offline or interactively. Secondly, the optimization model requires only minute tuning of model parameters during the beginning stage. Once initial tuning is done, it can be used to automatically segment a large collection of images that are distinct but, share similar features. It is proposed to conduct extensive experiments on various collections of biological images, it will be established that the model proposed is quite computationally efficient and effective for segmentation.

Keyword- *Biological image segmentation, Interactive Image segmentation, Microscopic images, multiple images*

I.INTRODUCTION

Image segmentation is the process of partitioning a digital image into multiple segments and used to locate objects and boundaries (lines, curves) in images. It is used in many areas, including computer vision, computer graphics, and medical imaging. Types of image segmentation are fully automatic image segmentation and Semi-automatic image segmentation. Completely automatic image segmentation has many intrinsic difficulties is still a very rigorous problem. For example, it is very often that an image can have much segmentation that is meaningful. Various Fields like medical or biomedical imaging, objects of interest (OOIs) are often badly defined and even sophisticated automatic segmentation algorithms often fail. Moreover, in cell segmentation in microscopy images and organ segmentation in medical images, the kind of object and segmentation of interest are known in advance. It is, therefore, enticing to design segmentation methods that allow the user to specify what the user wants.

For these situations, the only possibility until recently was to replace automatic methods by interactive ones, where a lot of interaction between the user and the image is necessary, either to draw the contours of OOIs. It is always very tiresome. So, it is replaced by semi-automatic image segmentation, with a very limited amount of user interaction. Many types of semi-automatic methods have been suggested: intelligent scissors, methods based on user steered image segmentation paradigms and methods based on the concept of fuzzy connectedness.

The segmented objects are clustered to retrieve the original image. In clustering there are three types of clustering. They are supervised, unsupervised and semi-supervised. Semi-supervised clustering is introduced to cover some drawbacks of clustering (unsupervised learning) and classification (supervised learning), such as production of non acceptable clusters or sometimes finding multiple grouping of data in the clustering process. In this situation semi-supervised clustering could be a good choice. Semi-supervised clustering uses some side-information to cover the categorization goal. The side-information could be the similar pairs from input data or information that indicates membership of the data items to specific clusters. This side-information usually has the pairs-wise (must-link and cannot-link constraints) form in most studies. Must-link constraints impose data on the same cluster but, cannot-link constraints impose them on different clusters.

In semi-automatic segmentation, the user marks some sample pixels from each class of objects. Then computational algorithm computes a classification of other pixels from each class of objects. This way, the resulting segmentation is highly controllable by the user and thereby eliminates much ambiguity in defining a partition. Because of this property it is used in medical field [2] & [3].

Initially optimization model is available for single class only. Later an optimization-based two-class segmentation model [4] is developed, in which an optimal class membership function is computed through the minimization of a quadratic cost function with user supplied samples as linear constraints. The basic idea is that two pixels should have similar membership if they are either geometrically similar or photo metrically similar or both. The results are quite impressive. The model was later extended [5] in to handle the multiple class problem. A few effective numerical optimization methods and fundamental theoretical properties of the model were studied [6], [7] & [8].

Single-image optimization models were extended to the multiple-image for image retrieval. The various clustering techniques are K-means and support vector machine. K-means is an unsupervised method used to group the objects based on attributes/features into K number of group. The grouping is performed by minimizing the sum of squares of distances between data and the corresponding cluster centroid. The drawback is user has to specify the number of clusters in advance, not able to handle noisy data and it is not suitable to discover clusters with non-convex shapes. Support Vector Machines is a supervised method, which is well suited for aspect based recognition images and color-based classification. SVM is widely used in object detection and recognition, Text recognition, etc the drawback is it's sensitive to noise, it considers only two classes and image classification problem exist.

The outline of this paper is as follows. In Section II, the proposed model and the properties are discussed. In Section III, the experimental result of the proposed model is shown. In Section IV, some concluding remarks are given.

II. PROPOSED SYSTEM

In this section, the formulation of the proposed model is stated. The two image-multiple class case is illustrated. This two image model can be used to segment collection of images one at a time. The generalization to multiple-image multiple class case is clear.

2.1 Optimization Model

Let u^s for s=1, 2 be two given multi channel images. The sizes are not necessarily the same. Let γ^s be the set of all pixels in image u^s. Let Ω^s be the set of whole unlabeled pixels in image. Let Γ^s be the set of pixels in image u^s labeled to one of the M classes by the user. Thus $\gamma^s = \Omega^s \cup \Gamma^s$ which allowing both labeled and unlabeled pixels contained in the image. The set of labeled pixels Γ^s is divided into $\Gamma^{s/1},\ldots,\Gamma^{s/M}$, where $\Gamma^{s/m}$ is the set of pixels that are labeled with class m, for m=1,…, M. s′ is an index referring to an image different from the image indexed by s. For each pixel I $\epsilon\ \gamma^s$ and each pixel j $\epsilon\ \gamma^{t,}$ let $w_{i,j}^{s,t} \geq 0$ be a similarity between the pair of pixels, for s, t=1,2. When t=s, the similarity $w_{i,j}^{s,t}$ is computed within image u^s; when t=s′, the similarity is computed across two images. For each i $\epsilon\ \gamma^s$, the similarity scores and normalized as shown in (1)

$$\sum_{j \in \gamma^s} w_{i,j}^{s,s} + \sum_{j \in \gamma^{s'}} w_{i,j}^{s,s'} = 1 \qquad (1)$$

For each pixel I $\epsilon\ \gamma^s$, let $N_i^{s,t} \subset \gamma^t$ be a set of pixels in image, which is called the neighbor of I in u^t. For each I $\epsilon\ \gamma^s$, let $\alpha_i^{s/m}$ ϵ [0 1] be the degree of membership of pixel i $\epsilon\ \gamma^s$ to class m. It is required that $\sum_{m=1}^{M} \alpha_i^{s/m} = 1$. It is also denote by the vector $(\alpha_i^{s/m})_{i \in \gamma^s}$. The basic idea is that the membership of similar pixels should be similar. For each unlabeled pixel i $\epsilon\ \Omega^s$, membership to class m inferred from its neighbors is weighted average as shown in (2)

$$\sum_{j \in N_i^{s,s}} w_{i,j}^{s,s} \alpha_j^{s/m} + \sum_{j \in N_i^{s,s'}} w_{i,j}^{s,s'} \alpha_j^{s'/m} \qquad (2)$$

Subject to the constraints,

$$0 \leq \alpha^{s/m} \leq 1 \text{ and } \sum_{m=1}^{M} \alpha^{s/m} = 1 \qquad (3)$$

For s=1,2 and m=1,…,M and the boundary condition $\alpha_i^{s/m} = 1$, for i $\epsilon\ \Gamma^{s/m}$ and $\alpha_i^{s/m}$

= 0, for i ϵ $\Gamma^{s} \backslash \Gamma^{s/m}$. The objective function in (2) can be compactly written in matrix form as shown in (4)

$$J(\alpha^1,\ldots,\alpha^M) = \sum_{m=1}^{M} \|DA\alpha^m\|_2^2 \qquad (4)$$

2.2. Similarity Measures

Two kinds of similarity measures are, geometric and photometric are. The former is based on pixel locations, whereas the latter is based on color features.

For each pixel i$\epsilon\gamma^s$, its geometric neighbor $G_i^{s,s} \subset \gamma^s$ is defined in (5)

$$G_i^{s,s} := \{j\epsilon\gamma^s : 0<\|i\text{-}j\|_\infty \leq r_g\} \qquad (5)$$

Where r_g>0 is a constant controlling the size of the window, and $\|.\|_\infty$ is the vector maximum norm. We often set r_g=1 so that a 3*3 window around pixel I is used.

The geometric similarity $g_{i,j}^{s,s}$ is defined in (6)

$$g_{i,j}^{s,s} := \begin{cases} c e^{-\|i-j\|_2^2/\sigma_i^2}, & \text{if } j\epsilon\, G_i^{s,s} \\ 0 & \text{, otherwise} \end{cases} \qquad (6)$$

Where e is a normalization constant such that, $\sum_{j\epsilon\gamma^s} g_{i,j}^{s,s}$ = 1, and σ_i^2 is computed as the sample variance of the geometric locations within$G_i^{s,s}$. For each pixel i$\epsilon\gamma^s$, let F_i be its feature vector.

The within image photometric neighbor $P_i^{s,s} \subset \gamma^s$ is defined to be the top 4 pixels within the 17*17 window around pixel whose feature vectors are nearest to F_i . Using a larger window size allows us to reduce error. The within image photometric similarity is defined in (7)

$$P_{i,j}^{s,s} := \begin{cases} c e^{-\|F_i-F_j\|_2^2/\rho_i^2}, & \text{if } j\epsilon\, P_i^{s,s} \\ 0 & \text{otherwise} \end{cases} \qquad (7)$$

Where, ρ_i^2 is computed as the sample variance of the photometric features within$P_i^{s,s}$.

For efficient computation of the across image photometric neighbor $P_i^{s,s'} \subset \gamma^{s'}$ the top 4 labeled pixels in pixels in S $\subset \Gamma^{s'}$ is considered, whose feature vectors are nearest to F_i. Here,S is a random sample of $\Gamma^{s'}$ such that it contains an equal number of pixels from $\Gamma^{s'}/1$ and $\Gamma^{s'}/2$. The across image photometric similarity is defined in (8)

$$P_{i,j}^{5.5} := c e^{-\|F_i-F_j\|_2^2/\theta_i^2}, \text{ if } j\epsilon P_i^{s,s'} \qquad (8)$$

Where, c is a normalization constant such that $\sum_{j\epsilon\gamma^{s'}} P_{i,j}^{s,s'} \equiv 1$, and θ_i^2 is computed as the sample variance of the photometric features within$P_i^{s,s'}$.

The within image neighbor and the across image neighbor are defined in (9) and (10) as

$$N_i^{s,s} := G_i^{s,s} \cup P_i^{s,s} \qquad (9)$$

$$N_i^{s,s} := P_i^{s,s'} \qquad (10)$$

The combined within image similarity and combined across image similarity is defined in (11) and (12)

$$w_{i,j}^{s,s} := (g_{i,j}^{s,s}/(1+\lambda) + \lambda P_{i,j}^{s,s}/(1+\lambda))/(1+\mu) \qquad (11)$$

$$w^{s,s'} = \mu P_{i,j}^{s,s'}/(1+\mu) \qquad (12)$$

Where, $\lambda > 0$ is a tuning parameter controlling the weight between geometric and photometric similarities, and μ >0 is a tuning parameter controlling the weight between within and across image similarities.

2.3. Optimality Conditions

The objective function in (4) is differentiated and Lagrange multipliers for the constraints is introduced in (3), to shown that the optimality conditions are given in the linear systems as shown in (13),

$$\tilde{A}\alpha^m = b^m \qquad \text{for } m=1,\ldots M \qquad (13)$$

$$\tilde{A} = I - D^T DW$$

$$= \begin{pmatrix} I - D_{\Omega^1}^T D_{\Omega^1} W^{1,1} & -D_{\Omega^1}^T D_{\Omega^1} W^{1,2} \\ -D_{\Omega^2}^T D_{\Omega^2} W^{2,1} & I - D_{\Omega^2}^T D_{\Omega^2} W^{2,2} \end{pmatrix}$$

$$b^m = \begin{pmatrix} b^{1/M} \\ b^{2/M} \end{pmatrix}$$

Each unlabeled pixel is connected to a labeled pixel through a sequence of directed edges, each of which connects a pixel to one of its neighbors in the same image or a different image. It shows that the solution is non singular and unique. If the matrix size is small, then linear systems can be efficiently solved by Gaussian elimination. However, if the image size is larger, preconditioned interactive methods [5] are used.

2.4. Applications to a Collection of Images

Suppose u^1 contains some manually labeled pixels while other images are unlabeled. To segment a large collection of images, we apply the optimization model to u^1 and other image (called u^2) at a time. That implies $\Gamma^1 \neq 0$ and Γ^2=0.

A simple way to apply the model is to let $P_i^{1,2}=0$ for all i ϵ γ^1, so that $W^{1,2}=0$, and let $w^{1,1}=G^{1,1}/(1+\lambda) + \lambda P^{1,1}/(1+\lambda)$.

In this case, the matrix is a block upper triangular as shown in (15)

$$\tilde{A}=\begin{pmatrix} I - D_{\Omega^1}^T D_{\Omega^1} W^{1,1} & 0 \\ -D_{\Omega^2}^T D_{\Omega^2} W^{2,1} & I - D_{\Omega^2}^T D_{\Omega^2} W^{2,2} \end{pmatrix} \tag{14}$$

The parameters λ and μ are manually tuned to solve $\alpha^{1/m}$ and the first unlabeled image. Then, these values are used to segment all other images. Thus the tuning is quite comportable for the collection that is used.

If there K>1 in images that contain labeled pixels, then we can simply apply the model for k+1 images to segment one unlabeled image at a time. The proposed model is easy to be extended. For the single image case, it show that α^m satisfies the strong maximum principle, which guarantees the strict in equalities $0< \alpha^m <1$ and the uniqueness of α^m [5]. For the multiple image, if $W^{1,2}=0$, then the feeble maximum principle, which implies $0\leq \alpha^m \leq 1$ only. However, the more important uniqueness of α^m still holds.

2.5. Computational Complexity

In optimization model, the computational costs is discussed in the following steps

Step1) Compute $P^{1,1}$(independent λ and μ)

Step2) Compute ^{1,1} (dependent on λ) and solve the linear system $[I- D_{\Omega}^{T_1} D_{\Omega^1} W^{1,1}]\, \alpha^{1/m} = b^{1/m}$ for m=1, 2... M-1.

Step3) Compute $P^{2,2}$ and $P^{2,1}$ (independent of λ and μ).

Step4) Compute $W^{2,1}$ and $W^{2,2}$(dependent on λ and μ) and solve the linear system $[I-D_{\Omega}^{T_2} D_{\Omega^2} W^{2,2}]\alpha^{2/m} = D_{\Omega}^{T_2} D_{\Omega^2} W^{2,1} \alpha^{1/m}$ for m=1,.,M-1.

During the initial tuning stage the parameters are tuned based on the labeled image and the first unlabeled image, steps 1 and 3 are needed to be performed only once, whereas steps 2 and 4 have to be repeated. In this experiment, steps 1 and 3 are often more time consuming than steps 2 and 4. If u^1 is fully labeled, then $\{\alpha^{1/1},\ldots, \alpha^{1/m}\}$ are known, and steps 1 and 2 can be skipped. Beginning from the second unlabeled image, only steps 3 and 4 are performed and no further tuning of parameters is done.

III. EXPERIMENTAL RESULTS

The nuclei cell test image is taken to segment one at a time using the proposed semi-supervised optimization model. The original image is a color image. It is having multiple levels of optimization model segmentation.

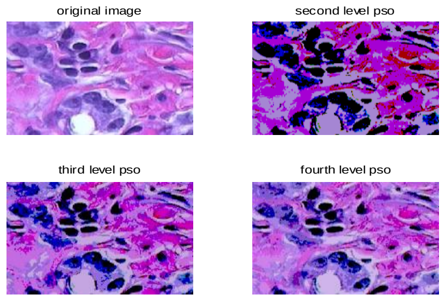

Figure 1: Segmentation of nuclei cell image obtained by pso optimization model

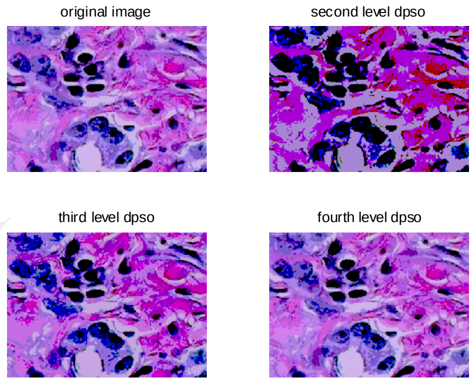

Figure 2: Segmentation of nuclei cell image obtained by dpso optimization model

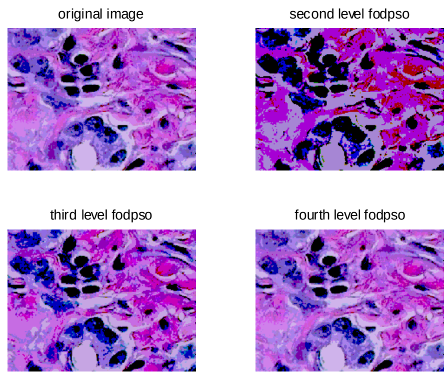

Figure 3: Segmentation of nuclei cell image obtained by fodpso optimization model

IV. CONCLUSION

A Semiautomatic optimization model for segmentation of multiple images is developed. The model has a quadratic objective function and linear constraints. Owing to the discrete maximum/

minimum principles, the optimality conditions simply boil down to solve the linear order. In our applications, the two parameters can be easily tuned. Once initial tuning is performed, the setup can be used to segment all other images within the collection automatically. The quality of the results is high. However, it relies on the logical supposition that the different classes can be separated in the feature space and that the user supplied samples can represent each class well.

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