Semi-Supervised Multi-Phase Image Segmentation and Application to Deep-Gray-Matter Segmentation in MRI Brain Images

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Abstract—Unsupervised image segmentations are usually implemented without human interactions, but the segmentation is sometime incorrect for complicated images, especially when the features of different classes are very close. On the other hand, supervised image segmentation, utilizing the features obtained by machine-learning and then applying some classification algorithms to the features, can usually get much more satisfying results. But supervised methods, are usually time-consuming, and only efficient for a specific type of data for each method. By a trade-off, semi-supervised segmentation integrates the advantages of both supervised segmentation and unsupervised segmentation.

In this paper, we proposed a semi-supervised multi-phase image segmentation framework which is motivated by image matting and central-gray-matter segmentation for magnetic resonance images (MRI). In our framework, an image is divided into two parts at the beginning, i.e., the known parts (labeled data) and the unknown parts (unlabeled data). The image segmentation is then to determine the unknown parts only. The class of a pixel in unknown part will be determined by not only its own features and the features of the known parts, but also its distance from the known parts. Experimental results demonstrate that our method outperforms unsupervised methods. Our method is also more efficient than supervised methods in the sense that there is no data required for training in order to obtain features for classification.

Keywords: Semi-supervised segmentation, multiphase segmentation, MRI brain image segmentation, Deep gray matter segmentation

1. Introduction

Unsupervised methods explore the intrinsic data features to partition an image into regions with different statistics. The segmentation procedure can be implemented using some assigned algorithm automatically without human beings’ interaction or interfering. Different from unsupervised segmentation, supervised image segmentation is a technique that classifies images using some assigned features for each class. These features usually obtained by machine learning due to the complexity of images. When image features are simple and able to be distinguished easily, supervised methods are not really necessary. However, when the image is much complicated, especially when the features of different classes are very close, unsupervised methods often fail to achieve a desired result. On the other hand, supervised image segmentation methods taking a learning procedure with a labeled training set to form a classifier, are likely to give a better result than unsupervised methods. However, marking the training set is very time-consuming.

The terms "supervised" or "unsupervised" comes from machine learning in computer vision. One typical example of unsupervised method is $k$-mean clustering. By only using image statistics, clustering algorithms partition an image in coherent groups without using labeled information. Most of the model-based segmentation methods belong to unsupervised methods. Many of them can still be viewed as an extension of clustering methods. Semi-supervised methods take a trade-off between supervised methods and unsupervised methods by inferring the classification from partially labeled data. The key difference between supervised learning and semi-supervised learning is that semi-supervised methods utilize the data features in both the labeled and unlabeled data points, while supervised learning only uses the features of labeled data. Hence, the main advantage of semi-supervised image segmentation methods is that they take advantage of the user markings to direct the segmentation, while minimizing the need for user labeling. There are several general approaches towards semi-supervised learning, but recent developments have mainly focused on graph-based methods under discrete settings, probably because the graph-based representation naturally copes with nonlinear data manifolds. In this formulation, data are represented by nodes in a graph, and the edge weights are given by some measure of distance or affinity between the data. Then, the labels for the unlabeled points are found by propagating the labels of labeled points through the graph. Based on this methodology, a number of methods have been proposed [1], [6], [10], [11], [12]. Paper [13] gives a survey of literatures on semi-supervised learning. However, except for [6], these methods are all for general data classification, none of which are developed specifically for image segmentations, probably because of their discrete settings.
Although in some papers, authors didn’t strictly distinguish semi-supervised methods and supervised methods, strictly supervised segmentation methods are actually quite different from semi-supervised segmentation methods. Generally speaking, the supervised segmentation sets up a learning machine before a segmentation is carried out. The learning process is performed at a large training set of the similar kind of data sets. Therefore, a strict supervised segmentation model is usually designed for a specific kind of images, such as cell segmentations, spine-segmentations, prostate segmentation, and so on. The learning procedure is usually carried out before the segmentation of such kind of images are performed. As soon as the learning procedure is finished, the features obtained can be used for segmentations of all such kind of images. Different from supervised segmentation, semi-supervised segmentation methods or interactive segmentation methods are carried out by interfering segmentation each time before an automatic segmentation procedure is performed.

Except for discrete settings, supervised image segmentation technique has also been embedded in continuous models. G. Gilboa and S. Osher [5] proposed a supervised segmentation model based on non-local information. N. Houhou et al. proposed a semi-supervised image segmentation method that relies on a non-local continuous version of the min-cut algorithm and labels or seeds provided by a user [6]. The segmentation process is performed via energy minimization. The proposed energy is composed of three terms. The first term defines labels or seed points assigned to objects that the user wants to identify. The second term carries out the diffusion of object and background labels and stops the diffusion when the interface between the object and the background is reached. The diffusion process is performed on a graph defined from image intensity patches. The graph of intensity patches is known to better deal with textures because this graph uses semi-local and non-local image information. The last term is the standard total variation (TV) term that regularizes the geometry of the interface.

Image matting is a 2-D interactive semi-supervised soft image segmentation technique for color images. In digital matting, a foreground element is extracted from an image by estimating a color and opacity for the foreground element at each pixel. The opacity value at each pixel is typically called its alpha, and the opacity image, taken as a whole, is referred to as the alpha matte (between 0 and 1) or key. Matting is used in order to composite the foreground element into a new scene. Matting and compositing were originally developed for film and video production. Some examples of image matting methods are Poisson Matting [9], Bayesian Matting [3] and Spectral Matting [8].

Formally, image matting methods take as input an image $I$, which is assumed to be a composite of a foreground image $F$ and a background image $B$. The color of the $i$-th pixel is assumed to be a linear combination of the corresponding foreground and background colors,

$$I_i = \alpha_i F_i + (1 - \alpha_i) B_i$$

where $\alpha_i$ is the pixel’s foreground opacity. In natural image matting, all quantities on the right hand side of the equation are unknown. Obviously, this is a severely under-constrained problem, and user interaction is required to extract a good matte. Most recent methods expect the user to provide a trimap as a start. Such an example is shown in Figure 1. The trimap is a rough (typically hand-drawn) segmentation of the image into three regions: foreground (shown in white), background (shown in black) and unknown (shown in gray). Given the trimap, these methods usually solve for $F$, $B$, and $\alpha$ simultaneously. This is typically done by iterative nonlinear optimization, alternating the estimation of $F$ and $B$ with that of $\alpha$. In practice, this means that for good results the unknown regions in the trimap must be as small as possible.

This paper is motivated by image matting and central-gray-matter segmentation for magnetic resonance (MR) brain images. It is a part of a large project "Biochemical Markers of Traumatic Brain Injury" supported by NIH (National Institutes of Health) grant. In a MR brain image, the intensities of white matter are usually greater than the intensities of gray matter. However, in the central area, the intensities of gray matter (called deep gray matter or central gray matter) are very close to white matter. Even worse, the intensities of central gray matter are usually greater than the intensities of white matter located in outer layer of brain. Therefore, in order to precisely segment MR brain images, supervised or semi-supervised image segmentation methods must be used. Just like image matting, existing semi-supervised image segmentations are mostly developed for two-phase images. In this paper, we developed a new semi-supervised multi-phase image segmentation framework based on the model developed in paper [4]. The following of this paper is organized as follows: Section 2 is an introduction to piecewise constant multi-phase soft segmentation model [4]. The model is then utilized to
develop a semi-supervised framework in Section 3, followed by the implementation in Section 4. Section 5 shows some fundamental experimental results. At the end is a short conclusion.

2. Multi-phase Soft Segmentation Model

Given a source image $I(x)$, we assume the image contains $N$ classes. Let $u_i(x)$ denote the $i$-th pattern and $p_i(x)$ be the $i$-th membership function. A piecewise smoothed soft Mumford-Shah model is defined as follow:

$$E(p; u) = \sum_{i=1}^{N} \frac{1}{2} \int_{\Omega} (I(x) - u_i(x))^2 p_i(x) dx + \sum_{i=1}^{N} \frac{\lambda}{1} \int_{\Omega} |\nabla u_i(x)| dx + \sum_{i=1}^{N} \frac{\mu}{2} \int_{\Omega} |\nabla p_i(x)| dx$$

(2)

The iterations based on fast gradient-descent method are

$$\begin{align*}
\frac{\partial E}{\partial u_i} &= - \lambda \text{div}(\frac{\nabla u_i}{|\nabla u_i|}) + (u_i - I) p_i \\
\frac{\partial E}{\partial p_i} &= - \mu \text{div}(\frac{\nabla p_i}{|\nabla p_i|}) + (u_i - I)^2
\end{align*}$$

(3)

The primal-dual form of (2) with respect to $u$ is

$$\min_{u} \max_{|v| \leq 1} E(u, v; p) = \sum_{i=1}^{N} \frac{1}{2} \int_{\Omega} (I(x) - u_i(x))^2 p_i(x) dx + \sum_{i=1}^{N} \frac{\lambda}{1} \int_{\Omega} u_i(x) \text{div} v_i dx$$

(4)

The primal-dual form of (2) with respect to $p$ is

$$\min_{p \in \Delta_{N-1}} \max_{|q| \leq 1} E(u; p, q) = \sum_{i=1}^{N} \frac{1}{2} \int_{\Omega} (I(x) - u_i(x))^2 p_i(x) dx + \sum_{i=1}^{N} \frac{\lambda}{1} \int_{\Omega} p_i(x) \text{div} q_i dx$$

(5)

The iteration on $u$ and $v$ is

$$\begin{align*}
\frac{\partial u_i}{\partial t} &= - [(u_i - I) p_i + \lambda \text{div} v_i] \\
\frac{\partial v_i}{\partial t} &= - \lambda \nabla u_i
\end{align*}$$

(6)

The iteration on $p$ and $q$ is

$$\begin{align*}
\frac{\partial p_i}{\partial t} &= - [(u_i - I)^2 + \mu \text{div} q_i] \\
\frac{\partial q_i}{\partial t} &= - \mu \nabla p_i
\end{align*}$$

(7)

3. From Unsupervised Segmentation to Semi-Supervised Segmentation

In an interactive semi-supervised image segmentation, an image is assumed to include two parts: the known part $\Omega_i$, $i = 1, 2, ..., N$ and the unknown part $\Omega_U$. Only the unknown part needs to be applied for segmentation. The above model is then to find segmentation only for the domain $\Omega_U$, i.e., to minimize the following energy functional:

$$E(p) = \sum_{i=1}^{N} \frac{1}{2} \int_{\Omega_U} (I(x) - u_i(x))^2 p_i(x) dx + \sum_{i=1}^{N} \frac{\lambda}{1} \int_{\Omega_U} |\nabla u_i(x)| dx + \sum_{i=1}^{N} \frac{\mu}{2} \int_{\Omega_U} |\nabla p_i(x)| dx$$

(8)

If we solve this problem still using previous procedures (6) and (7), then it is not a supervised segmentation since we didn’t use any known information to instruct segmentation for the unknown area. The key point of our work is to update each pattern $u_i$ based on the nearest point principle, i.e.,

$$u_i(x) = \text{average}\{u_i(y) | y = \text{arg}\min_y \{x - y, y \in \Omega_i\}\}$$

(9)

which is referred from the third step of Poisson Matting [9].

With initially given patterns $u_i(x)$ and under smoothness constraint of $p_i(x)$, the objective energy functional becomes

$$E(p) = \sum_{i=1}^{N} \frac{1}{2} \int_{\Omega_U} (I(x) - u_i(x))^2 p_i(x) dx + \sum_{i=1}^{N} \int_{\Omega_U} |\nabla p_i(x)| dx$$

(10)

where each $u_i(x)$ is determined by (9).

Considering that the close relation of points when they are near to each other and the loose relation when they are far away, we add a distance factor to the fitting term. The energy functional is therefore becomes

$$E(p) = \sum_{i=1}^{N} \frac{1}{2} \int_{\Omega_U} (I(x) - u_i(x))^2 p_i(x)e^{\alpha d_i(x)} dx + \sum_{i=1}^{N} \int_{\Omega_U} |\nabla p_i(x)| dx$$

(11)

where $\alpha$ is a parameter and $d_i(x)$ is the nearest distance from each pixel $x$ to the $i$-th unknown area $\Omega_i$. The factor $e^{\alpha d_i(x)}$ will force the influence to be ignored when the distance of a point $x$ from a known area $\Omega_i$ is far away.

Correspondingly, we rewrite the energy with indication functions and replace the total variation by weighted total
variation, we get the final energy functional
\[
E(p) = \sum_{i=1}^{N} \int_{\Omega} (I(x) - u_i(x))^2 p_i(x)e^{\alpha d_i(x)}\chi_{\Omega_i}(x)dx \\
+ \sum_{i=1}^{N} \mu \int_{\Omega} |\nabla p_i(x)| g(\nabla I(x))\chi_{\Omega_i}(x)dx
\]
where \(\tilde{I}\) is a smoothness of \(I\) and \(g(x_1, x_2)\) is an edge function usually defined as \(\frac{1}{1 + x_1^2 + x_2^2}\).

4. Solving Semi-Supervised Multi-phase Image Segmentation

The primal-dual form of (12) is
\[
E(p) = \sum_{i=1}^{N} \int_{\Omega} (I(x) - u_i(x))^2 p_i(x)e^{\alpha d_i(x)}\chi_{\Omega_i}(x)dx \\
+ \sum_{i=1}^{N} \mu \sup_{q_i \in K} \int_{\Omega} p_i(x)\text{div} (g(\nabla \tilde{I}(x))\chi_{\Omega_i}(x)q_i(x))dx
\]
where \(K = \{\phi \in C^1_c(\Omega, \mathbb{R}^2) : |\phi| \leq 1\}\).

So, the iteration on \(p\) and \(q\) are, respectively,
\[
\frac{\partial p_i}{\partial t} = -[(u_i - I)^2 e^{\alpha d_i}(x)\chi_{\Omega_i}(x) \\
+ \mu \text{div} (g(\nabla \tilde{I}(x))\chi_{\Omega_i}(x)q_i(x))]
\]
\[
\frac{\partial q_i}{\partial t} = -\mu(\nabla p_i)g(\nabla \tilde{I}(x))\chi_{\Omega_i}(x)
\]
In our framework, the new memberships \(p_i(x)\) obtained from above iterations are actually a temporary one. We still need to update the memberships based on the following rule:
if \(p_i(x) > 0.95\) and \(I(x) \approx u_i(x)\) for some \(1 \leq i \leq N\) and \(x \in \Omega_U\), then put \(x \to \Omega_i^+\). So, the known parts are updated by
\[
\Omega_i = \Omega_i \cup \Omega_i^+.
\]
Correspondingly, the unknown part is updated according to the following equation
\[
\Omega_U = \Omega - \bigcup_{i=1}^{N} \Omega_i
\]
We now describe the complete algorithm. Given an image \(I\) defined in a domain \(\Omega\), if the image contains \(N\) classes, then the complete algorithm for our semi-supervised multi-phase image segmentation is given as below.
1) Initialization.
   a) Initialize known parts \(\Omega_i^0\) using brush;
   b) Initialize unknown part by \(\Omega_U^0 = \Omega - \bigcup_{i=1}^{N} \Omega_i^0\);
   c) Initialize memberships: For each \(1 \leq i \leq N\) and \(x \in \Omega_i^0\), set \(p_i^0(x) = 1\) and \(p_j^0(x) = 0\) for \(j \neq i\); for \(x \in \Omega_U^0\), set \(p_i(x)\) randomly.
   d) Initialize patterns: For each \(1 \leq i \leq N\) and \(x \in \Omega_U^0\), set \(u_i^0(x) = I(x)\); for any \(x \in \Omega_U^0\), set \(u_i^0(x)\) in terms of the nearest point principle as (9);
2) Iterations.
   a) Update memberships \(p_i^k(x)\) by (14);
   b) Update known areas \(\Omega_i^k\) by (15);
   c) Update unknown area \(\Omega_U^k\) by (16);
   d) Update patterns \(u_i^k(x)\) by (9);
3) Termination The iterations will be terminated if \(\Omega_U = \emptyset\)

5. Experimental Results

We carried out several experiments to show the efficiency of our method. In Figure 2, we show how semi-supervised algorithm works differently from general unsupervised segmentation. The original image contains two objects with same intensities as shown in Figure 2(b). Suppose that only the left one is the object that we need to separate from the background. Under unsupervised segmentation methods, the segmentation of the foreground will be exactly the same as shown in Figure 2(b). However, if we circle a green mask as the seed for the background and circle a red mask as the seed for the foreground as shown in Figure 2(a), then the segmentation of the foreground is shown as in Figure 2(c), which is the desired one.

![Fig. 2: Principle of semi-supervised segmentation: (a) Original image with masks. (b) Original image and unsupervised segmentation. (c) Supervised segmentation.](image)

In Figure 3, we present a comparison of a flower segmentation using supervised segmentation and unsupervised segmentation. Note that the central part of the flower is same dark as the background. If we use unsupervised segmentation model, the central part of the flower will be classified as background (see the central part of (b1)). With semi-supervised method, the segmentation result is perfect (see the central part of (b2) and compare it with the central part of (b1)).

Figure 4 shows the shrinking procedure of the unknown area in the first 10 iterations in the flower segmentation, where dark areas are unknown areas, from where we can see how fast the iterations converge. For a 240 × 240 image, the iterations take around 8 seconds. However, if we use the corresponding unsupervised method, the iterations will take around 68 seconds under same converge settings.
5.1 Application to deep-gray-matter segmentation of MRI brain images

The method developed in this paper is actually motivated by the requirement of deep-gray-matter segmentation in MRI brain images. The deep-gray-matter (sometimes called central-gray-matter) in MRI brain images is hard for segmentation due to its intensity much different from the general gray matter and very close to the intensity of white matter. We use the developed method to segment deep-gray-matter from MRI brain images and obtained ideal result.

In Figure 5, we show the comparison between unsupervised method and supervised method, as well as the comparison between using more known areas and using less known areas. We use an MR brain image as an example. It is well known that the central gray matter (or deep gray matter) has very similar intensities to the white matter’s intensities. The first row is the segmentations with the unsupervised segmentation method; the second row is the segmentations with the supervised segmentation method but with less known area; the third row is the segmentations also with the supervised segmentation method but with more known area; and the last row is the segmentations obtained first with the unsupervised method and then fixed under experienced doctors’ instructions. In the first row, (a1) is the original image, and (b1) through (d1) are the segmentations of cerebrospinal fluid (C.S.F), gray matter and white matter, respectively. In the second row, (a2) is the original image with less assigned class masks, and (b2) through (d2) are the segmentations of C.S.F, gray matter and white matter, respectively. In the third row, (a3) is the original image with more assigned class masks, and (b3) through (d3) are the segmentation of C.S.F, gray matter and white matter, respectively. In the last row, (a4) is the image with a mask drawn with hand by experienced doctors, and (b4) through (d4) are segmentations obtained with the unsupervised segmentation method and then fixed with the masks drawn in (4a).

From the results, we can easily see that supervised segmentation is always better than unsupervised segmentation, and supervised segmentation with more labeled area is better than the result with less labeled area. Figure 5(b4-d4) is the result obtained by unsupervised segmentation first and then fixed under the instruction of experienced doctors. So, (b4-d4) can serve as ground truth data. We can see that the supervised segmentation results (b3-d3) are very close to the ground truth. Meanwhile, with choosing some area from just SINGLE slice of the image, we can use supervised method to segment ALL slices of a 3-D MRI brain image very well. In this way, a lot of time can be saved.

6. Conclusion and future work

This work is motivated by MR brain image segmentations which is one part of our previous project. The project has been closed in the summer of 2012. It is well known that in the central area of a MR brain image, the intensities of gray matter is usually very close to the intensities of white matter. Sometimes (actually very often), the intensities of central gray matter is bigger than the intensities of white matter...
not located in the central part. If we only use unsupervised segmentation methods, we can’t obtain the desired result.

The framework of semi-supervised image segmentation discussed in this paper is still based on intensity. When the image contains some texture features, the framework does not work very efficiently. In this case, feature-based model must be used in the framework. Let $F : \omega \subset \mathbb{R}^n \rightarrow Z \subset \mathbb{R}^m$ be a function which maps an $n$-dimensional image domain to a multi-dimensional ($m$-dimensional) space of contextual features $Z$. For each point $x \in \omega$, $F(x)$ is a vector containing image statistics or features. Such features can encode contextual knowledge about the region of interest and its neighboring structures (e.g., size, shape, orientation, relationships to neighboring structures, etc.). Feature-based image segmentation is extensively used in texture segmentation and some medical image segmentation. Therefore, an immediate future work is to develop a feature-based semi-supervised multiphase image segmentation framework. Please address any questions related to this paper to Hongyuan Wang by Email (hywang@cczu.edu.cn).

References