

Critical Review

In the paper “A variational framework for integrating segmentation and registration through active contours”, Yezzi et al have developed a method to simultaneously segment and register features from multiple images by using active contours. They tested this method on brain and spine data to register / segment across CT and MRI images. In their paper they discuss both 2D and 3D algorithms and the results of the tests they have carried out. They conclude the paper with their results from synthetic data to evaluate the method.

Paper Significance:

New registration and segmentation methods are becoming more dependent on each other. If the images are segmented first, the resulting contours are used to solve rigid body and non-rigid body registration problems. Segmentation can also depend on registration when images are segmented with the help of a model that provides higher level information such as shape, appearance and relative geometry. To use this information, the images should first be registered to aid segmentation. (Yezzi 171-172)

All the methods have inherent uncertainties. Error propagation between multiple steps diminishes the reliability of the end result. Combining the registration and segmentation steps eliminates the intermediate processes so the solutions to both can be built simultaneously.

Overview of the Algorithm:

The algorithm consists of using energy functionals from two or more images to deform the contour and update the registration model used to correspond the two images. This is repeated until it converges to a steady value. The energy functionals for the two images are:

$$E_1(C) = \int_{c_{in}} f_{in}(\mathbf{x})d\mathbf{x} + \int_{c_{out}} f_{out}(\mathbf{x}) d\mathbf{x},$$
$$E_2(\hat{C}) = \int_{\hat{c}_{in}} \hat{f}_{in}(\mathbf{x}) d\mathbf{x} + \int_{\hat{c}_{out}} \hat{f}_{out}(\mathbf{x}) d\mathbf{x},$$

The method uses region based energy functionals instead of edge based. These functionals assumes that the value of each pixel can be represented with a Gaussian distribution which takes into account the noise in the image. Therefore the f corresponds to:

$$f_{in} = (I - u)^2, \quad f_{out} = (I - v)^2,$$
$$\hat{f}_{in} = (\hat{I} - \hat{u})^2 \quad \text{and} \quad \hat{f}_{out} = (\hat{I} - \hat{v})^2,$$

where u and v are the mean intensity values inside and outside the contour respectively.

At each step, the energy inside and outside the contours is calculated and added together to obtain the total energy. This equation is manipulated to calculate the integrals over one contour only so that the energy is optimized with respect to that one contour. The equations needed to solve this problem are:

$$\frac{\partial C}{\partial t} = (f(\mathbf{x}) + m\hat{f}(g(\mathbf{x})))N - \kappa N,$$

$$\frac{dg_i}{dt} = \int_C \hat{f}(g(\mathbf{x})) \left\langle \frac{\partial g(\mathbf{x})}{\partial g_i}, mRM^{-1}N \right\rangle ds.$$

where g is the affine transformation with the form:

$$g(\mathbf{x}) = RM\mathbf{x} + D.$$

where R is the rotation matrix, M is the scaling factor and D is the translation.

Evaluation and Criticisms:

This is a useful algorithm to segment and register multiple images at the same time. The fact that it uses region based energy functionals instead of edge-based makes the algorithm applicable to medical images where the edge information may not be easily extractable. The energy functionals also take into account the noise in the image by assuming that the value of each pixel can be represented with a Gaussian distribution which makes the algorithm more robust against noise. Therefore it can be used when the image quality is lower. This saves time and money spent on acquiring high resolution images to get accurate results.

As I have mentioned before, the algorithm solves both the segmentation and registration problem at the same time. As we can see in Figure 9 of the validation experiments, only segmenting the images without registration may not be accurate when Gaussian noise is introduced. This experiment is repeated by using the suggested algorithm. As we can see in Figure 10, both of the images converge to an accurate representation of the contours. The reason for this is that the algorithm aims to optimize the energy constraint for the two images at the same time. Therefore if one of those

images has better contrast, it can be used to account for the extra noise present in the second image. One thing suspicious in this experiment is that the test images used in these two experiments have different levels of Gaussian noise introduced. The experiment with only segmentation have higher amount of noise whereas one of the pictures in the second experiment is crisper. The lack of explanation of the image choice makes the reader wonder about the result if the algorithm is run on the pictures of the first experiment.

Relevance to Our Project:

When building an atlas, images from a population are segmented and registered onto a tetrahedral mesh. The resulting warped volume is used in the statistical analysis step to calculate the variation of the population from the mean structure. In the current pipeline, this registration / segmentation step is done by using a method called Mjollnir. This method can also be implemented to carry out this step. Even if this algorithm does not prove to be as efficient as Mjollnir, the equations in the paper provided insight into active contours and how energy functionals are used to deform contour lines.

Another application would be to segment and register the patient data onto the segmented preliminary atlas created from the Hong Kong data set. The cadaver images are easier to segment because there is no tissue around the bones to provide any complication for the algorithms. Therefore the segmentation of the patient data set can be aided with the pre-segmented volume of the cadaver study if this algorithm is used.

Another strength of this algorithm is the fact that it can be used for registering and segmenting images between different imaging modalities. If we wanted to improve the atlas by using patient data from various modalities, this algorithm may prove useful.

One thing to note is that if we wanted to incorporate this to our project, we would have to use the binary template image previously segmented. The pixel values in this image would either be 0 or 255. If this is represented with a Gaussian distribution, the sigma would be 0, which contradicts the assumptions made while building the algorithm. To implement this, we would have to introduce Gaussian noise into the segmented template.

Another problem in using a template for segmenting is the fact that what we are using images from various patients who have anatomical differences, which can make it harder to optimize the energy constraints and can miss important edge data.

Possible Improvements:

In the paper it is mentioned that to keep things clean and simple, the case of registering and segmenting only two images are discussed. In our case it would be more useful to generalize the algorithm to be used for multiple images so that the algorithm can be implemented efficiently.

Another improvement mentioned on the paper is the concept of using a weighted combination of E_1 and E_2 where one image would be easier to segment than the other. In our case it is obvious that the template image would be easier to segment than the rest of the patient data. Therefore the weight of the template can be higher to make the segmentation / registration easier.

Bibliography:

Yezzi, A. Zollei, L. Kapur, T. A variational framework for integrating segmentation and registration through active contours. *Medical Image Analysis* 7 (2003) 171 – 185.