Medical Image Analysis, handin 2

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1 Medical image segmentation

1.1 Segmentation introduction

Segmentation is the process of dividing an image into meaningful regions with similar properties. It provides great contribution to the medical image field and it attracts most of the interest in the community. There are two main different segmentation methods: supervised and unsupervised methods. The first group uses databases of segmented organs to train some algorithms, and the extracted knowledge is used to annotated previously unseen images. The second group is designed to use some common sense and logic and doesn't require a large collection of annotated data. Medical image segmentation is used, most often in combination with other tools, in different applications, such as automation of manual work, computer aided diagnosis, image guided procedures, and motion analysis.

In automation of manual work, segmentation can be used to segment organs to better understand human anatomy. Using segmentation algorithms, it is possible to speed up the process and achieve a better accuracy than manual standard procedures. One example is the segmentation of organs for radiation therapy planning, where segmentation is used to plan the emission of beams of intense energy to kill cancer cells. In fact, it can be used to shoot beams from different direction in such a way that they are all centered at the tumor, therefore delivering an high dose of radiation to the tumor and minimizing the radiation delivered to the surrounding structures. Also, since different human organs are known to have different radiations dose sensitivity, we can use segmentation to segment all organs, estimate their volumes, and plan the treatment taking into account how much dose of radiations each organ will receive.

In computer aided diagnosis, segmentation can be applied to medical images for the prediction of diseases. For example, in cardiomegaly, doctors uses height and width of the heart, measured from x-rays images, to estimate the presence of the disease state. Segmentation can be used to segment the whole heart and obtain an estimation of its volume, therefore providing a better accuracy than standard procedures. Another example is the detection of vertebrae fractures, where standard procedures involve the measurement of the height of the vertebrae at different points, to estimate vertebral compression. In this regard, segmentation can be used to automatically measure the level of compression of the bone by segmenting the whole vertebrae, achieving better accuracy in the compression fracture prediction. Lastly, it can also be used to generate automated reports, such as the annotation of the exact position of a suspicious object (which, for example, might indicates the presence of a tumor) in a given medical image.

Segmentation can also be used in image guided procedures, such as the insertion of medical screw into the patient vertebrae. This delicate procedure is needed to artificially straighten the spine according to the anatomical requirement of the patient body. Segmentation can help the doctor to know the anatomy of the patient, which is essential to position the screw perfectly in the vertebrae. Another application of segmentation in image guided procedures is the planning of dental implants. Since the jaw shows left-right symmetry, segmentation can be used to reconstruct the anatomy of a missing tooth, by segmenting the same tooth at the other side of the jaw. Also, it can be used to visualize the anatomy and the position of the nerves, therefore guiding the insertion of screw into patient's jaw.

Lastly, segmentation can also be used in motion analysis, where certain modalities, such as ultrasound images or cine magnetic resonance images, can be segmented to better understand the organs motion pattern.

1.2 Dilation and erosion

Dilation and erosion are two elementary dual morphological operations, which are often used in combination with more sophisticated algorithms to solve problems in medical image analysis. Dilation expands a binary mask by removing one (or more) layer of pixel, therefore holes enclosed by a region and gaps between different regions become smaller, and small intrusions into boundaries of a region are filled in. Erosion produce the opposite effects, it shrinks a binary mask by adding one (or more) layer of pixel, therefore the holes and gaps between different regions become larger, and small details are eliminated. One of their application is the contour extraction, which can be obtained by both operations.

The combination of dilation and erosion operations is a compound operation namely morphological opening, if erosion is applied before dilation, and morphological closing, if vice versa. In fact, the result of erosion and dilation is greatly influenced by the order of the operations, which is problem specific and it depends by the objective and by size and shape of the structuring elements. Both morphological compound operations can be used in segmentation problems to remove internal noise, and smooth the boundaries of the segmentation mask. Their difference is that morphological opening has the effect of separating connected objects and removing small objects, while morphological closing can connect disconnected objects and fill small holes caused by noise.

Fig 1 shows the effect of morphological closing (third image, from left to right) applied to an incomplete lung field mask (second image). We can see that, after a series of five dilations and erosions, the vessels are included in the lung field mask (except for one vessel which might be included by performing one extra iteration) and the boundaries became smooth. In the lung segmentation example, morphological closing can also be used to obtain the segmentation of the lung vessels. This is possible by subtracting the extracted incomplete lung field mask (second image in Fig 1) from the smooth lung field mask (third image in Fig 1), and then performing the extraction of the components representing the vessels. In the same example, morphological opening could be useful to remove boundary artifacts, which, for example, might occur in case the air in the stomach get connected to the lung field mask.

Morphological opening and closing present different risks. Using morphological opening on narrow structuring elements presents the risk that the initial erosion operation might disconnect some regions. Therefore, for example, it should not be used for the segmentation of the brain blood vessels shown in Fig 2 (on the left), because it might disconnect them or delete some fine details. While morphological closing it is not used when different regions are located closely, because there is the risk that the first iteration of dilation might connect them. Therefore, for example, it should not be used for the segmentation of the brain shown in Fig 2 (on the right), because it might close up the folds.

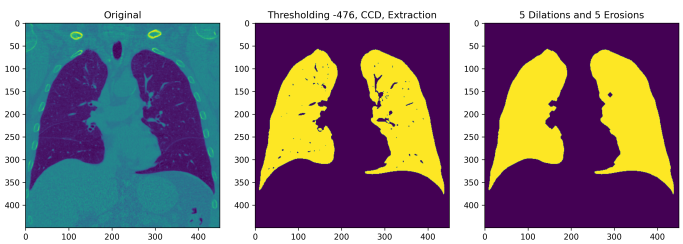

Fig. 1. Thresholding, CCD, dilation and erosion. From left to right, the first image is a cross-section of a lung computed tomography image. The second one is the incomplete lung field mask obtained after performing thresholding ($t = -476$), connected component decomposition (CCD), and extraction of the first two largest components. The last image is the result of the application of a sequence of 5 morphological closing (5 dilations and 5 erosions) to the incomplete lung field mask.

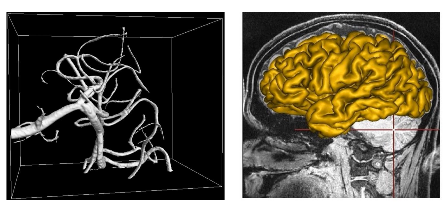

Fig. 2. Segmentation of brain and brain blood vessels. The figure shows a segmentation of brain blood vessels, on the left, and a segmentation of the brain, on the right.

1.3 Graph cut and random walker

Graph cut algorithms are a group of graph based algorithms that have been successfully applied to a wide range of problems in computer vision and graphics. These tasks involve an energy minimization that can be approximated by solving a maximum flow problem in a graph, and therefore by finding the minimum cut. In MIA they are used for the segmentation of objects, nowadays mainly to augment other methods and not as independent algorithm. A graph cut algorithm can be used to segment an object (e.g. an organ) by finding the minimal cut that pass through its boundary. This is possible by setting the capacities of the edges connecting neighbouring pixels, as inversely proportional to the difference in intensity between these pixels, and by adding seeds points inside the object of interest and terminal points to part of the image that do not belong to it (e.g.

background). Therefore, graph cut segmentation methods offer the advantage that they can be easily corrected by the user by adding extra seeds or terminal points and performing few extra iterations. The disadvantage is that it naturally works only with images containing one object of interest and the background.

Another successful graph based algorithm is the random walker (RW). In RW multiple seed points are added to objects of interest, and the main idea is that the probability of the random walker to move, from a pixel to a neighbouring one, is inversely proportional to the difference in intensity between the two pixels. Therefore, a label is assigned to each pixel according to the seed point that the pixel can reach with highest probability (or the seed point that, after many iterations, the random walker usually reach from that pixel), considering all possible paths. RW has been applied to different problems in computer vision and graphics, but in MIA it is used for 2D and 3D medical image segmentation. It offers the advantage of being able to perform the complete segmentation of different objects with a relative low effort from the user. In fact, it usually requires a relative small number of seed points defined by the user, or alternatively, statistical information about the seed points position, to perform a complete segmentation of different objects. The disadvantage of RW is that is not suited for the segmentation of very long and narrow structuring elements, e.g. the lung airways. In fact, by performing narrow and long walks, at each step there is a small probability that the walker move to a pixel with a large difference in intensity, therefore there is an higher chance that the walker can leave the object of interest to enter another one (e.g. the background).

1.4 Random walker implementation

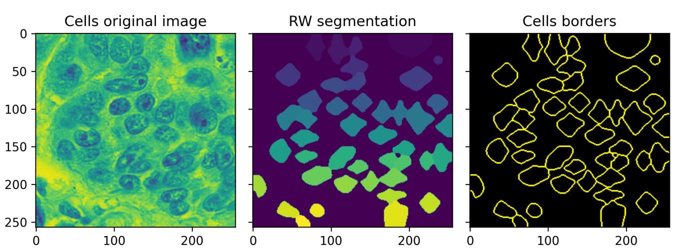

Fig. 3. Random walker on 2D image. From left to right, the figure shows the original 2D cell image, the random walker segmentation, and the cells borders obtained by applying morphological operations.

Fig 3 shows the individual segmentation of cells in a 2D image. Connected component decomposition (CCD) was applied to the object mask to obtain a different pixel value for each cell. The resulting image was merged with the background mask, and the merged image was used as seed points for the RW segmentation. The border of the cells was obtained by subtracting the result of morphological erosion from the result of morphological dilation. Fig 4 shows the segmentation of the mandible in a 3D head-and-neck (HaN) computed tomography image. In this case, the object of the segmentation was only one, therefore CCD was not needed. The object mask was added to the background mask and the merged image was used as seed points for the RW segmentation of the mandible. Then, the mandible border was obtained applying the morphological operations to the 3D segmented image.

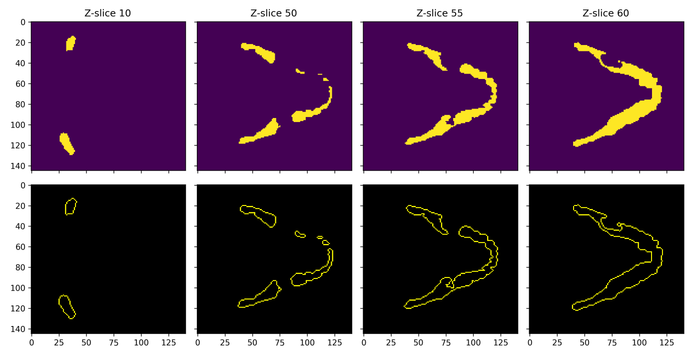

Fig. 4. Random walker segmentation on 3D image. The figure shows five z-slices of a 3D HaN computed tomography image. The first row shows the segmentation of the mandible, obtained by applying the RW algorithm. The second row shows the mandible border, obtained by applying morphological operations to the RW result.

1.5 PCA in medical image segmentation

PCA is a mathematical method used to represent, or project, high dimensional data into low dimensional space. The new dimensions are defined by the principal components, or eigenvectors, in such a way that the variance of the projected data points is maximized. Therefore, this technique allows the visualization of high dimensional data in two dimensions, but it is also used as preprocessing step before the application of many machine learning algorithms and in many other applications. In MIA, one application of PCA is the medical image segmentation, i.e. through active shape model (ASM) using landmark positions, statistical appearance model (SAM) using object intensities, and active appearance models (AAM) using a combination of both.

ASM is a supervised segmentation model based-method able to handle noisy data. It requires several data sets of manually segmented images, which are fitted to a random set of points. In the case of 3D data, the correspondences between the landmarks of the surfaces are estabilished and the landmarks are aligned using Procrustes analysis. The latter applies the optimal Euclidean similarity transformation, i.e. translation, rotation, and scale, to minimize pointwise differences between objects and a selected reference. Then, PCA is used to build a statistical shape model from the training shapes, and active shape model segmentation of new images can be performed. Basically, as shown in Fig 5, new PCA models can be generated by adding eigenvectors and their captured variance to the mean shape. Therefore, starting from the mean shape as initial guess, using PCA, the object shape model is iteratively deformed to fit newly localized landmark positions on the new image.

SAM is similar and related to the ASM method, but instead of taking advantage of landmark positions it uses PCA to model object intensities and perform texture based segmentation. While AAM takes advantage of both object intensities and shapes.

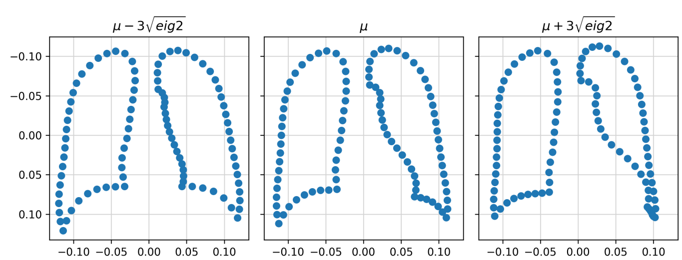

Fig. 5. PCA shape model variations. The figure shows lung field shape variations obtained by adding and subtracting the second eigenvector and its captured variance to the model mean shape.