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Abstract

In this paper a fully automated segmentation system for the femur in the knee in Magnetic Resonance Images and the brain in Single Photon Emission Computed Tomography images is presented. To do this several data sets were segmented manually. The resulting structures were first represented by unorganised point clouds. With level set methods surfaces were fitted to these point clouds. The iterated closest point algorithm was then applied to establish correspondences between different surfaces. Both surfaces and correspondences were used to build a three dimensional statistical shape model of the major bones in the knee. The resulting model is then used to automatically segment structures in subsequent data sets through three dimensional Active Shape Models. The result of the segmentation is promising, but the quality of the segmentation is dependent on the initial guess.

1 Introduction

Hospitals today produce numerous diagnostic images such as Magnetic Resonance Imaging (MRI), Single Photon Emission Computed Tomography (SPECT) and Computed Tomography (CT). These images are often noisy and thus hard to segment.

Active Shape Models (ASM) is a segmentation algorithm that can handle noisy data. Cootes et al. have in [2] used ASM to segment out cartilage from two dimensional MR images of the knee. But the MR images are produced in three dimensions and it would be of interest to get a three dimensional representation of the structures.

To do this several problems have been solved. First surfaces have been fitted to unorganised point clouds through a level set method. After that corresponding parametrisations are established over the training set with the Iterated Closest Point (ICP) algorithm. The next step is to build the shape model with Principal Component Analysis (PCA). Finally the model is used to segment new images.

2 Shape Reconstruction

Point clouds of the structures are constructed by manual segmentation. This generates noisy point clouds. To handle the noisy point cloud representation of the structures a level set approach is used to reconstruct the surface. In [5] Zhao et al. developed a method which reconstructs a surface that is minimal to the distance transform to the data set. This approach is problematic when the point clouds are noisy. Later Shi and Karl [3] proposed a data-driven, Partial Differential equation (PDE) based, level set method that handles noisy data. This method is used to fit a surfaces to the noisy point clouds.

3 Finding Correspondences

In shape modeling it is of great importance that during the training a dense correspondence is established over the training set. This part of the process is the most difficult and the most important for a good result of the upcoming segmentation.

The traditionally way to solve this is to place landmarks at the surface. Another approach to find correspondence between shapes is to have corresponding parametrisation of the shapes. If the shapes later are sampled according to the parametrisation it is possible to find corresponding points of two shapes. In the remaining part of this paper these points are refried to as landmarks.

3.1 Iterative Closest Point

In this paper the correspondence of points over the training set is established by the ICP algorithm [1].

The ICP algorithm gives corresponding triangulations of the surfaces over the training set.

The ICP algorithm matches two surfaces. It uses one as source surface and one as target. The triangulation of the source is kept and the aim is to get a corresponding triangulation on the target surface. This is done bye the following iterative process:

1. For each vertex at the source surface find the closest point at the target surface.

2. Compute and apply the transformation from the source to the new points that minimise the mean square error between the two point clouds with translation and rotation.

3. Return to 1 until the improvement is less than a threshold value $\tau > 0$.

If the same source surface is always used and the target surface is switched it is possible to find corresponding landmarks in a larger training set.

4 Aligning the Training Set

When the corresponding landmarks are found the next step is to align the landmarks under similarity transformations. This is done because only the shape should be considered in the shape model and the translation, scale and rotation should be filtered out.

Alignment of two shapes in three dimensions can be calculated explicitly. Umeyama presents a way to do this in [4].

In this paper not only two data sets but the whole training set is to be aligned. Therefore an iterative approach proposed by Cootes et al. [2] has been used.

When the corresponding points are aligned it is possible to move forward and calculate a shape model of the knee.

5 Building the Shape Model

With n landmarks, $\mathbf{X}_i = (\mathbf{x}_1, \ldots, \mathbf{x}_n)^T$ where $\mathbf{x}_i$ are m-dimensional points, at the surface. The segmentation problem is nm dimensional. It is therefore of great interest to reduce the dimension and in an accurate way be able to decide whether a new shape is reasonable.

The aim is to find a model so that new shapes can be expressed by the linear model $\mathbf{x} = \bar{\mathbf{x}} + \mathbf{\Phi b}$, where $\bar{\mathbf{x}}$ is the mean shape, $\mathbf{\Phi}$ is the shape modes and $\mathbf{b}$ is a vector of parameters for the shape modes. With this approach it is possible to constrain the parameters in $\mathbf{b}$ so the new shape always will be reasonable.

To generate the model $\mathbf{\Phi}$ and constrains for the parameters $\mathbf{b}$ from N training shapes PCA is applied [2].

5.1 Constructing New Shapes

From the model new shapes can be constructed. Let $\mathbf{\Phi} = [\mathbf{\Phi}_1, \ldots, \mathbf{\Phi}_N]$, where $\mathbf{\Phi}_i$ are the eigenvectors of the covariance matrix used in the PCA. New shapes can now be calculated as

$$\tilde{\mathbf{x}} = \bar{\mathbf{x}} + \mathbf{\Phi b} = \bar{\mathbf{x}} + \sum_{i=1}^{N} \mathbf{\Phi}_i b_i. \tag{1}$$

Cootes et al. propose in [2] a constraint of the b_i parameters of $\pm 3\lambda_i$, where λ_i is the square root of the eigenvalues of the covariance matrix σ_i, to ensure that any new shape is similar to the shapes in the training set. This method is used in this paper.

It is not necessary to choose all $\mathbf{\Phi}_i$, but if not all are used those corresponding to the largest eigenvalues are to be chosen. The numbers of shape modes to be used in the shape reconstruction can be chosen to represent a proportion of the variation in the training set. The proportion of variation that the first t shape modes cover are given by,

$$V_t = \frac{\sum_{i=1}^{t} \sigma_i}{\sum \sigma_i}. \tag{2}$$

6 Segmentation with ASM

The segmentation with active shape models is based on an iterative approach. After an initial guess the four steps below are iterated.

1. Search in the direction of the normal from every landmark to find a suitable point to place the landmark in.

2. Update the parameters for translation, rotation, scale and shape modes to make the best fit to the new points.

3. Apply constrains on the parameters.

4. Repeat until convergence.

6.1 Multi-Resolution Approach for Active Shape Models

To improve the robustness and the speed of the algorithm a multi-resolution approach is used. The idea of multi-resolution is to first search in a coarser image and then change to a more high resolution image when the search in the first image is not expected to improve. This improves the robustness because the amount of noise is less in the coarse level. The high resolution images are then used to find small structures. The speed accelerates because there is less data in the coarse levels.

6.2 Getting the Initial Guess

In order to obtain a fast and robust segmentation it is important to have a good initial estimation of the position and orientation. In the initial guess the shape is assumed to have the mean shape. This makes it necessary to find values of seven parameters to make a suitable initial guess in three dimensions (three for translation, one for scale and three for the rotation).

6.3 Finding Suitable Points

To find the new point to place a landmark, while searching in the directions of the normal, models of the variations of appearance for a specific landmark l is build. Sample points in the normal direction of the surface are evaluated. These values usually have a big variation of intensity over the training set. To minimise this effect the derivative of the intensity is used. The sampled derivatives are put in a vector $\mathbf{g}_i$. These values are then normalised by dividing with the sum of absolute values of the vector.

This is repeated for all surfaces in the training set and gives a set of samples $\{\mathbf{g}_i\}$ for each landmark. These are assumed to be Gaussian distributed and the mean $\bar{\mathbf{g}}$ and the covariance $\mathbf{S}_g$ are calculated. This results in a statistical model of the grey level profile at each landmark.

Through the process from marking the interesting parts of the knee to building the triangulation with corresponding landmarks of the object small errors in the surface will probably be introduced. This will make the modeled surface to not be exactly suited to the real surface. Thus the profiles will be translated a bit and the benefit of model will be small. To reduce these problems an edge detection in a short distance along the normal to the surface is performed. If the edge detection finds a suitable edge the landmarks are moved to that position.

6.3.1 Getting New Points

When a new point is to be located, while searching in the direction of the normal during segmentation, the quality of the fit is measured by the Mahalanobis distances given by

$$f(\mathbf{g}_s) = (\mathbf{g}_s - \bar{\mathbf{g}})^T \mathbf{S}_g^{-1} (\mathbf{g}_s - \bar{\mathbf{g}}), \tag{3}$$

where $\mathbf{g}_s$ is the sample made around the new point candidate. This value is linearly related to the probability that $\mathbf{g}_s$ is drawn from the model. Thus minimising $f(\mathbf{g}_s)$ is the same as maximising the probability that $\mathbf{g}_s$ comes from the distribution and therefore that the point is at the sought-after edge.

To speed up the algorithm only a few of the landmarks are used in the coarse levels. 1/4 of the landmarks were kept for every step to a coarser level.

6.4 Updating Parameters

When new landmark positions are located the next step is to update the parameters for translation, scale, rotation and shape modes to best fit the new points. This is done by an iterative process. The aim is to minimise

$$\|\mathbf{Y} - T_{t,s,\theta}(\bar{\mathbf{x}} + \mathbf{\Phi b})\|^2, \tag{4}$$

where $\mathbf{Y}$ is the new points and T is a similarity transformation. The iterative approach follows the one presented by Cootes et al. in [2].

In the segmentation only shapes relatively similar to the shapes in the training set are of interest. Therefore constraints are applied to the $\mathbf{b}$ parameters. The used constraints are $\pm 3\sqrt{\sigma_i}$ where σ_i is the eigenvalue corresponding to shape mode i.

7 Experiments

The algorithm were used on two data set, MR images of the knee and SPECT images of the brain.

7.1 Finding Corresponding Points

If the left or the right knees were mirrored in the left-right direction of the patient it was possible to use both left and right knees at the same time to build the model.

A source to make the result worse was that the images did not cover exactly the same area in the top. That made the surfaces sometimes cover a larger part of the femur in the knee images and in the brain images the whole brain was not always covered. This means that there are no true corresponding point on the surfaces. Because of this it arise strange artifacts, on the top of the femur and in the lower part of the brain, on some shapes.

7.2 Segmentation

The result of the segmentation showed big difference between the MR images and the SPECT images. The result was significantly better on the SPECT images.

7.2.1 Results for MR Images of the Knee

When the initial guess was not good enough the model was not able to find the way to the femur. Instead other edges were located that were of no interest (often the edge of the image).

If the initial guess was good enough the search algorithm found the right edges almost every time. But in some parts of the images the result was not as good. During the segmentation only the sagittal images were used and if the result were visually examined the result looked better in the sagittal view. In Figure 1 the result is viewed.

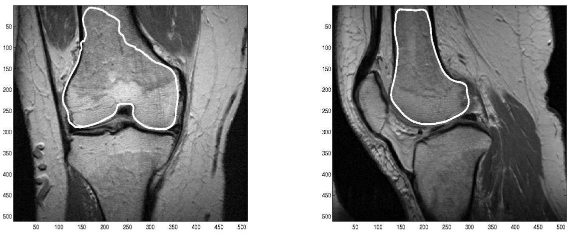

Figure 1: The result of the segmentation when the model of the gray level structure were used. The segmentation was applied in sagittal images and the result looks better in the sagittal view.

7.2.2 Results for SPECT Images of the Brain

When the segmentation was done on the SPECT images a better result was obtained, see Figure 2. When the algorithm was used on a number of brains and the result was compared to the points marked on the surface it was hard to tell which were the choice of the computer and which were chosen by the expert.

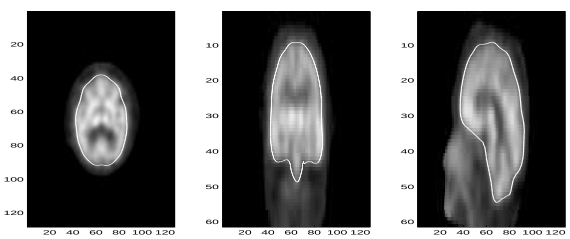

Figure 2: The result of the segmentation on SPECT images of the brain.

8 Summary and Conclusions

In this paper we present a fully automated way to segment three dimensional medical images with active shape models. The algorithm has been tested at MR images of knees and SPECT images of the brain. The results are promising especially in the SPECT images. In the MR images it is harder to find a good initial guess which makes the result not so good as in the SPECT images. But if the initial guess is good the segmentation algorithm usually gives a satisfying result.

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