Deformable Templates for Feature Extraction from Medical Images

P.Lipson (A.I. Lab, M.I.T.), A.L.Yuille (D.A.S. Harvard), D.O'Keeffe (M.G.H.) J.Cavanaugh (M.G.H.), J.Taaffe (M.G.H.), D.Rosenthal (M.G.H.)

Abstract

We propose a method for detecting and describing features in medical images using deformable templates, for the purpose of diagnostic analysis of these features. The feature of interest can described by a parameterized template. An energy function is defined which links edges in the image intensity to corresponding properties of the template. The template then interacts dynamically with the image content, by evaluating the energy function and accordingly altering its parameter values. A gradient maximization technique is used to optimize the placement and shape of the deformable template to fit the desired anatomical feature. The final parameter values can be used as descriptors for the feature. Measurements of intensity values within a region of the template can be used as inputs to a medical diagnostic system. We have developed a Picture Archive and Communication System (PACS) based image analysis program which employs the technique of deformable templates to localize features in dual energy CT images. Measurements can then be automatically made which can be used for maintenance of patients suffering from bone loss and abnormal marrow fat content. This system has been successfully tested on 552 (69×8) images and is currently in use at Massachusetts General Hospital, Boston, MA. Statistical comparisons between the system and previously used manual techniques show that their performances are practically equivalent and that the system has several advantages over the human operator, for example, consistency, accuracy and cost.

1 Introduction

Feature extraction of structures from medical images is a significant and complex problem. Automated localization of anatomical parts may be useful to clinicians by relieving labor intensive processes and increasing the accuracy, consistency, and reproducibility of image interpretations. However, such automated localization processes are often hindered by the irregular attributes of the medical structures and the imperfect scanning procedures.

It is desirable to have representations for the anatomical parts and a recognition process that are able to adapt to irregularities in both the object structure and in the image content (i.e. noise). Thus, both the feature representation and the localization procedure must be sufficiently general in order to accept variations of the same object and sufficiently specific in order to be able to differentiate the desired object from all others. One idea, developed by Yuille, Cohen, and Hallinan (1989), is to represent the desired object by a deformable template, an isomorphic parametric model that embodies the ideal characteristics of, and the *a priori* knowledge about, the object. The localization process involves altering the parameters of the template in such a way that it maximizes an energy function or measure of fit. The apparent dynamic interaction between the template and the image causes the template to be mapped on to the desired object. We have found that the concept of deformable templates can be applied to create a dynamic and robust algorithm for the localization of medical structures from digitized Computer Tomography images.

We have utilized an extension of the theoretical template method in an application to localize automatically the vertebral trabecular bone and then to measure the attenuation coefficients of this structure as well as the Cann-Genant calibration samples contained within CT images. The measurements are used to determine the trabecular bone density and fat percentage. Bone mineral content and fat percentage are used clinically to diagnose and monitor patients suffering from bone loss and abnormal marrow fat content, as occur in osteoporosis and Gaucher disease. Two factors which are crucial to the successful long term maintenance of these patients are accuracy and consistency in the measurement techniques. Presently, time-consuming and tedious manual methods are used to obtain the trabecular bone and calibration samples' attenuations. In order to reduce radiologists' time commitments and to enhance patient maintenance, we have developed a PACS based image analysis program which automatically performs accurate and reproducible measurements upon dual energy CT images.

In section 2 we describe deformable template models in general. In section 3 we show how to construct the deformable template model for this specific example and describe its dynamics. Section 4 describes the details of the implementation and section 5 gives the results on the database of 552 images (69 patients with 8 images per patient).

This work is described in more detail in Lipson et al (1989) with many illustrations of the deformable template in action.

2 Deformable Templates

Deformable templates (DTs) have some similarities with elastic deformable models (Burr 1981a, 1981b, Durbin and Willshaw 1987, Durbin, Szeliski and Yuille 1988), and to snakes (Kass, Witkin and Terzopolous 1987, Terzopolous, Witkin and Kass 1987) (see also applications to medical imaging, principally to construct 3D objects, by Ayache et al. 1989, Chen et al. 1989, Vandermeulen et al. 1989). There are, however, three important differences: (i) DTs embody *a priori* knowledge about the feature being detected, (ii) the structural forces on the DTs are global rather than local (preventing many local minima), and (iii) DTs can be easily implemented (since they involve only a small number of parameters) and give a compact description of the feature.

Grenander and his collaborators (Chow et al. 1989, Knoerr 1989) have represented the boundaries of two-dimensional natural objects in terms of a Markov model. This is somewhat similar to the snake approach, except they use *a priori* knowledge about the features, found by statistical analysis of the shapes of the objects, rather than assuming the structures are thin plates and membranes. Staib and Duncan (1989) also recommend this approach.

3 The Ellipsoidal Template and the Energy Function

Axial cross sectional CT images of the spine yield approximately elliptical vertebral contours. Thus, we have utilized an isomorphic ellipsoidal template as a feature detector. This ellipsoidal template is mapped on to the vertebra and is constrained within the boundaries of the cortical bone. The region anterior to the spinal cord within the elliptical template accurately describes the vertebral trabecular bone.

An ellipse can be represented by five parameters. These parameters include the major and minor axes (a and b), the x and y coordinates of the center point ($\vec{c} = (c_x, c_y)$), and the orientation angle (θ). The equation for an ellipse with these parameters is

$$\{\frac{(\vec{x}-\vec{c})\cdot\vec{n}}{a}\}^2+\{\frac{(\vec{x}-\vec{c})\cdot\vec{n}^*}{b}\}^2=1,\quad where\ \ \vec{n}=(\cos\theta,\sin\theta)\ \ \vec{n}^*=(-\sin\theta,\cos\theta) \tag{1}$$

The value of the energy function that is maximized during the feature detection is a function of the template's five parameters.

Let $I(x,y)$ be the intensity at the point (x,y) in an (filtered, edge extracted) image. The *Total Energy* TE_p with respect to the perimeter of the ellipse is

$$TE_p(\vec{c},\theta)=\int_0^{2\pi} I(x,y)\{a^2\sin^2\psi+b^2\cos^2\psi\}^{1/2}d\psi \tag{2}$$

where $x=c_x+a\cos\psi\cos\theta-b\sin\psi\sin\theta$ and $y=c_y+a\cos\psi\sin\theta+b\sin\psi\cos\theta$.

Each parameter is updated according to its contribution to the change in total energy function with respect to the change in time. For the five parameters the update rules are

$$\frac{da}{dt}=KE_a\frac{\partial TE_p}{\partial a},\ \frac{db}{dt}=KE_b\frac{\partial TE_p}{\partial b},\ \frac{dc_x}{dt}=KE_{c_x}\frac{\partial TE_p}{\partial c_x},\ \frac{dc_y}{dt}=KE_{c_y}\frac{\partial TE_p}{\partial c_y},\ \frac{d_\theta}{dt}=KE_\theta\frac{\partial TE_p}{\partial\theta}. \tag{3}$$

Lipson et al (1989)A gives explicit forms for the derivatives of TE_p with respect to the parameters a, b, c_x, c_y, θ.

The values for the constants KE are dependent upon the size and steepness of the gaussian field. Typical initial values of the constants, for an image processed with a large steep gaussian field (for long range interactions), are $(KE_a, KE_b, KE_{c_x}, KE_{c_y}, KE_\theta) = (1/7290, 1/7290, 1/7290, 1/7290, 1/36000000)$. Typical initial values of the constants for an image processed with a small shallow gaussian field (for precise localization) are $(KE_a, KE_b, KE_{c_x}, KE_{c_y}, KE_\theta) = (1/20250, 1/20250, 1/20250, 1/20250, 1/26000000)$.

4 The Algorithm

The automatic analysis program must localize and measure five areas of interest in each image. The first area is the vertebral trabecular bone. The other four areas are contained in the Cann-Genant calibration phantom. The phantom is easily recognized by psearching the image for the two high attenuation steel rods placed at either end of the phantom as markers. The vertebral trabecular bone is localized using the method of deformable templates.

The algorithm to localize the vertebral trabecular bone has several stages. First, the vertebra must be detected. A preprocessing stage estimates the size and location of the vertebra by analyzing the image edge data. These estimates are used to determine initial values for the parameters of the ellipsoidal template. The ellipsoidal template is then applied to the binary edge data, extracted using a sobel operator, which has been convolved with a Gaussian filter, with large standard deviation, to give an edge field. This field is largest at the original edge data and acts to attract the template towards these edges. The template, within the edge field, is deformed in such a way as to maximize the total energy or goodness of fit over the perimeter of the ellipse. Deformation takes place over 40 iterations. The mapping of the template to the vertebral contour is further refined, for better localization, by deforming the ellipse on the same binary image which has been convolved with a smaller shallower Gaussian field. This second deformation takes place over 15 iterations. Once the template is fitted to the vertebral contour, it is automatically scaled down to avoid overlap with any edges of the high intensity cortical outline. A measure of the trabecular bone is invalid if made in a region containing both trabecular and cortical bone. The final stage transfers the template from the processed image to the original CT image. The average attenuation coefficient of the region anterior to the spinal cord within the template is measured. This region, which represents the vertebral trabecular bone, is marked in black on the original image for a later visual quality control inspection.

5 The Results

Application of the technique to 69 patients (8 images per patient) led to correct localization in all but two cases (see later this section). It yielded attenuation coefficient measurements (in hounsfield units) differing by less than 1 percent from manually derived values. :$(ENERGY(kVP), SLICE, CORRELATION) = (80, A, 0.970), (140, A, 0.968), (80, B, 0.988),$

$(140, B, 0.988), (80, C, 0.984), (140, C, 0.986), (80, D, 0.986), (140, D, 0.990).$

The calculated values for individual bone density in mg/c.c. show a correlation of .989 for single energy bone mass (80kVp), .990 for dual energy bone mass(140kVp), and a .980 for the 2 line linear fit between the 80kVp and 140kVp. Values for the vertebral fat percentage show a correlation of 0.868. Concentration based on fit to 80kVp data is 0.989. Concentration based on fit to 140kVp data is 0.990. Concentration based on linear fit between 80kVp and 140kVp is 0.980. Fat percentage is 0.868.

Plots of the automatic vs. manually derived values, in addition to analysis of variance and parameter estimation (slope and intercept of plots, mean of the difference between the two sets of values), are given in Lipson et al (1989).

There were two clear sets of cases where the algorithm was unable to correctly localize the vertebral trabecular bone. The first case occurs when the patient shows signs of a calcified aorta. The calcified aorta appears as a high intensity closed ring anterior to the vertebra. The second case occurs when the part of the spine, connected to a vertebra from a higher level, appears as a disconnected, large, high intensity cluster. In both cases, the ellipsoidal template is attracted to the anomalous features. Clearly, the current template is an insufficient model for feature detection in these instances.

The model could be extended to contain smaller ellipses (not greater than two cm on either axis) anterior and posterior to the original template. These two new additions would be constrained to have the same orientation as the original ellipse. Additional parameters include the distance from each of the two new templates to the original template.

The automated analysis program is currently being used by the Department of Radiology at the Massachusetts General Hospital, Boston, MA.. It was incorporated into a Picture Archive and Communications System (PACS), which has been patented with a trade name uRSTAR (O'Keeffe et al. 1989).

6 Conclusion

In conclusion, deformable templates and energy functions can be easily adapted to the irregularities both of the imaging process and the geometric variabilities of anatomical features in medical images. Deformable templates have proved, in a sample of over 552 images, to be a sufficient method for localization of the vertebral trabecular bone in order to measure its average attenuation coefficient. For the most part, it seems that the template representation and dynamic interaction process can be easily adapted to other medical structures.

The detailed relevance of this system to medical imaging and diagnostics is reported elsewhere (Lipson et al. 1990). This describes how statistical comparisons between the system and previously used manual techniques show that their performances are practically equivalent. Additionally, the advantages of the automated technqiue over manual techniques, including consistency, accuracy, and cost, are described.

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