IMAGE RECONSTRUCTION AND OBJECT CLASSIFICATION IN CT IMAGING SYSTEM

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ABSTRACT

By obtaining a feasible filter function, reconstructed images can be got with linear interpolation and filtered backprojection techniques. Considering the gray and spatial correlation neighbour informations of each pixel, a new supervised classification method is put forward for the reconstructed images, and an experiment with noise image is done, the result shows that the method is feasible and accurate compared with ideal phantoms.

Keywords Filter function, Backprojection, Image reconstruction, Fuzzy clustering, Object classification

1 INTRODUCTION

Many types of computerized tomography (CT) scanners have been developed. But they are mostly used for medical diagnosis, no industrial CT (ICT) system has been made in China by now. The technique of CT is now extensively used for industrial nondestructive evaluation abroad, especially in America.

In a number of imaging modalities, including CT, SPECT, PET and in some cases, projection data are acquired, and images are reconstructed utilizing tomographic reconstruction algorithmss[1−3].

This image reconstruction and processing algorithms are focussed on building an applied ICT system. A better reconstruction method adopted is first filtering projection data for correcting the origin data, then feasible linear interpolation, finally the backprojection reconstruction processes. For the reconstructed images, the destination is to find the objects wanted. But, in the practical reconstructed images, there are noises and some errors, in order to keep true objects and not to make new errors, usual image processing, such as filtering is not used here. So, an improved object classification method is put forward based on fuzzy clustering segmentation, and more accurate experimental results are got.

2 IMAGE RECONSTRUCTION ALGORITHM

The two-dimensional CT problem is considered here. Supposing that $f(x,y)$ is the linear attenuation coefficient in one fixed plane section (x,y) of a tested object, $P(t,\theta)$ the integral of f along the line $L(t,\theta)$, *i.e.*,

$$P(t,\theta) = p_f(L(t,\theta)) = \int_{L(t,\theta)} f\,\mathrm{d}s \tag{1}$$

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where $L(t,\theta)$ is the line whose normal goes through the origin making angle θ with the positive x-axis and hasing length $t(-\infty < t < \infty)$, $L(t,\theta)$ is the line:

$$x\cos\theta + y\sin\theta = t \tag{2}$$

$P(t,\theta)$ is equal to the two-dimensional Fourier transform[4] of f in polar-coordinates, *i.e.*,

$$\hat{P}(\omega,\theta) = \hat{f}(\omega,\theta) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} f(x,y)\exp[i\omega(x\cos\theta + y\sin\theta)]\mathrm{d}x\mathrm{d}y \tag{3}$$

If $P(L)$ is known for all lines L, then f is given by Eq.(3) and the Fourier inversion formula, *i.e.*,

$$f(x,y) = (1/4)\pi^2 \int_{o}^{\pi} \mathrm{d}\theta \int_{-\infty}^{\infty} \hat{P}(\omega,\theta)\exp[i\omega(x\cos\theta + y\sin\theta)] \mid \omega \mid \mathrm{d}\omega \tag{4}$$

where the $\mid \omega \mid$ comes from the transformation of the Jacobian into polar-coordinates.

With calculating, one can obtain a discrete reconstruction formula f_Φ depending on Φ, given by

$$f_\Phi(x,y) = (a/2n)\sum_{j=0}^{n-1}\sum_{k=-\infty}^{\infty} p(t_k,\theta_j)\Phi(x\cos\theta_j + y\sin\theta_j - t_k) \tag{5}$$

where $t_k = kd$, $k = 0, \pm1, \pm2, \ldots$ and $\mid k \mid \leq 1/d$; $j = 0, 1, \ldots, n\text{-}1$, n is the number of views; d is the ray spacing distance between parallel rays in each view.

We spent a lot of time on finding the filtering function[5] Φ

$$\Phi(kd) = -4/[\pi d^2(4k^2 - 1)], k = 0, \pm1, \pm2, \ldots \tag{6}$$

The projection data $p(t_k,\theta_j)$ are generated according to the requirements of the upper algorithm, the reconstructed images of objects can be got and mapped into the VGA pictures with 64 gray level.

3 IMPROVED CLUSTERING SEGMENTATION AND CLASSIFICATION METHOD

The reconstructed images in CT are accurate in most cases, but sometimes, because of the effects of noises and limited projection data, the images have errors. In order to get right physical quantities about the objects tested, the errors must be corrected.

In object recognition, the interesting objects from the background are usually extracted, it is one of most extensively used methods [6–9] that threshold segmentation at gray histogram, in fact, is a peak-seeking problem. This method considers the two-peak distribution of image gray histogram, and there is a peak valley between the two peaks, when peak valley is adopted as the threshold value, segmentation is the best. But, in actual image, because of the effects of noises etc, the gray histogram may not appear obvious peaks standing for the objects and the background. At this time, selected threshold is not precise, the segmentation result with it may bring many errors. An improved object image segmentation and classification method is described in the paper based on iterative self-organizing datum analysis techniques of fuzzy clustering segmentation[10], this improved method uses average sample iteration technique to determine clustering centre, and divides the unknown objects into a few types with the clustering centre, and obtains classification image using supervising rule of Freeman code. The explanation is given as follows:

Let a set X include N samples, divide N samples into C types. Every sample is divided into one type according to its membership grade. So, correlation partitioning matrix can be given, *i.e.*

$$E = (\mu_{ij})_{C\times N} \tag{7}$$

satisfies (1) $\mu_{ij} \in [0,1]$, μ_{ij} indicates membership grade of x_j that is subordinate to ith type; (2) $\sum_{i=1}^{C} \mu_{ij} = 1$, $\forall j$; (3) $\sum_{i=1}^{N} \mu_{ij} > 0$, $\forall i$. Each matrix E satisfying above conditions correlates with one type of C fuzzy partition, all fuzzy partitioning matrices consist of fuzzy partitioning space, *i.e.*

$$M_{fc} = E/\mu_{ij} \in [0,1], \forall i,j; \quad \sum_{i=1}^{C} \mu_{ij} = 1, \forall j; \quad \sum_{j=1}^{N} \mu_{ij} > 0, \forall i \tag{8}$$

In order to get the best partition, one hopes that

$$J(E,V) = \sum_{j=1}^{N}\sum_{i=1}^{C} \mu_{ij} \mid x_j - V_i \mid^2 \tag{9}$$

reaches minimum value. Here, V_i is ith clustering centre (i=1, 2, ..., C), $\mid x_j - V_i \mid^2$ is distance square sum between jth sample and V_i that jth sample is subordinate to. Usually, it is difficult to get the minimum of $J(E,V)$, $J(E,V)$ can be simplified as

$$J_m(E,V) = \sum_{j=1}^{N}\sum_{i=1}^{C} (\mu_{ij})^m \mid x_j - V_i \mid^2 \tag{10}$$

where m is parameter to be selected. Obviously, in order to get the best segmentation result, one should get the solution (E,V) while $\min\{J_m(E,V)\}$.

To overcome the difficulty of getting the solution of $\min J_m(E,V)$, one can use the following iterative formulae to calculate,

$$\mu_{ij} = \sum_{k=1}^{C} [\mid X_j - V_i \mid / \mid X_j - V_k \mid]^{-2/(m-i)} \tag{11}$$

$$V_i = [\sum_{j=1}^{N} (\mu_{ij})^m X_j] / \sum_{j=1}^{N} (\mu_{ij})^m \tag{12}$$

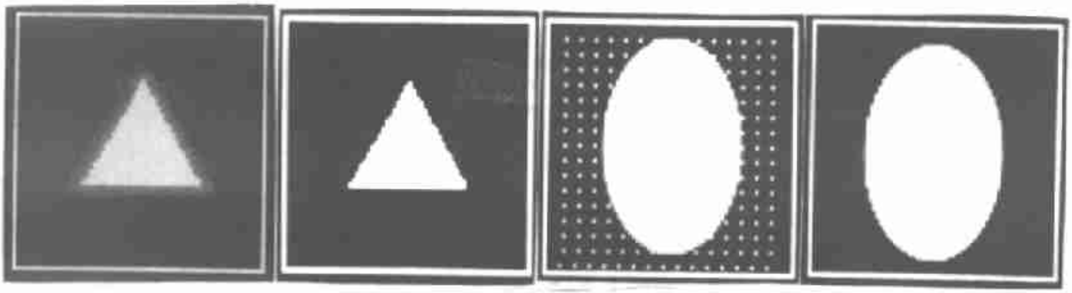
Through the upper clustering method, the objects are divided C types, but when each pixel is classified according to its membership grade, there will be errors because of noise etc. Considering the special limit of the reconstructed image, a supervised object classification method is presented here, it is that object classification based on not only the gray but also spatial information. Freeman eight direction code is utilized as the supervising regulation, if a pixel (i, j) has over four continuous and same clustering membership grades, it is divided into this type, otherwise, this pixel is considered non-object and not classified to any types. The classification rule is if $| X_j - V_{io} | = \min_i | X_j - V_i | \wedge$ Freeman rule, then X_j is i_oth type. The supervised classification method avoids possible error object classification effectively.

4 EXPERIMENTS AND DISCUSSION

Above methods are utilized to set up an experimental system on IBM-PC/386 using Microsoft C6.0 programming language. Rotation view with angle 180^o is divided by 60, there are 100 lines per view to generate parallel-beam projections. And we have obtained four phantoms with 64×64 images with 64 gray-level. These figures are explained as follow as:

Fig.1 is reconstructed images of a square that its edge length is 0.9; Fig.2 a ring that its inner and outer radii are 0.5 and 0.9. Since the projection data are better, the

Figs 1–3 Reconstructed imags of a square, ring, and triangle with edge noise, one by one



Figs 4–7 Clustering image of triangle with improve method, object classification of the triangle, reconstructed image of ellipse with grid noise, classification result of the ellipse, one by one

images are accurate. Fig.3 gives a reconstructed image of triangle with edge fuzzy noises, its edge length is longer than truth 1.0; Fig.4 shows the clustering image of the triangle through two iteratations, it is divided three types: one is the centeral triangle that is true object, another is triangle edge frames, the third is background. Their classification image of the true and precise triangle is shown in Fig.5 with the improved object classification. Fig.6 shows an reconstructed ellipse image with grid noises, these noises firstly are clustered as that of true object too, but through the improved method of supervising rule, they are omitted while the image is classified. Fig.7 gives the correct classification image.

5 CONCLUSIONS

The results demonstrate that the reconstructed images of square and ring are excellent. But, because the projection data of the triangle and the ellipse that we generate are added with noises purposely, these images are not precise, we used the improved clustering image segmentation and object classification methods to segment images and to classify object, the result images are very accurate compared with ideal phantoms.

The methods described in the paper are aimed at application of image reconstruction and processing in the parallel-beam geometry. And these methods are utility for other cases. We will finish image reconstruction from fan-beam projection data in not longer future.

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