Study on Image Recognition Application Based on Multi Features Fusion

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Abstract—**From low to high, information fusion can be divided into three levels. The feature-level fusion not only keeps the most original information, but also overcomes the unstable and large characteristics of original data. In this article, we take six types of B ultrasound liver images as the research objects, and with multi-feature fusion technology and its application in medical image recognition, made in-depth study on feature extraction of image color, texture and shape, and then apply them in multi-features fusion.**

Keywords- Image Recognition; Multi Feature Fusion; Feature Extraction

I. INTRODUCTION

With the development of computer technology, Information fusion technology has become a new data processing technique. Information fusion technology has been phenomenal growth in the past 10 years, and entered many application fields. Image fusion is an important branch of information fusion technology, including three levels: pixel level, feature level and decision level. Its major application directions are shown in Figure 1:
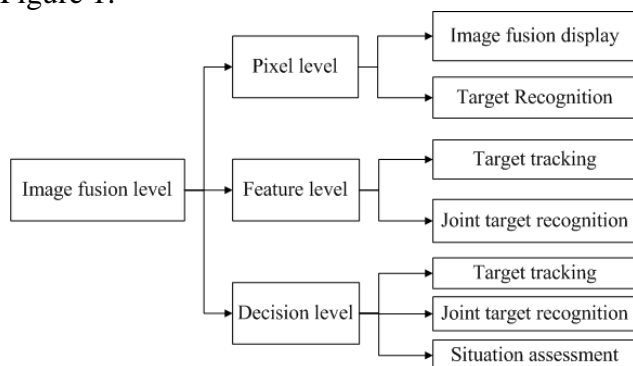

Figure 1. Application Fields of Image Fusion

Currently, image information fusion technology is widely used in military target recognition, medical diagnostics, remote sensing, computer vision, and weather forecasts, etc. Feature level image fusion can be divided into fusion target state information fusion and target feature fusion. Among them, target state information fusion is mainly used in the field of multi sensor target tracking, while target feature fusion is joint target recognition in feature level, which fusion method still involves pattern recognition technologies, but must carries on related processing of the feature before fusion. What's more important, in the field of pattern recognition, image processing and computer vision, people have do in-depth study on feature extraction and characteristics-based clustering problem. In fusion process, people often use fuzzy method, neural network technology, clustering method and Kalman filter, etc. The methods of fused image feature extraction can be divided into three categories: a) fusion of various image features in a single image; b) multi-image fusion of similar sensor in one scene; c) multi-image fusion of different sensing mode.

Medical image and common image is very different, due to its high gray resolution, large amount information, heterogeneity and noise significance characteristics. And Existing feature extraction methods still cannot well express the content of medical images. To solve this problem, in this article, we are committed to medical image feature extraction of color, texture and shape features, and based on application of principal component analysis (PCA) in feature level fusion, to analyze the liver B-ultrasound image recognition.

II. Image Feature Extraction

A. Image Acquisition

The medical images we collected are 385 B ultrasound liver images, including six categories of hepatocellular carcinoma, hepatic cyst, liver hemangioma, fatty liver, hepatic congestion and normal liver. All the images are collected with the same ultrasound equipment, with JPEG format and 768×57 resolution. The six types of liver images are shown in Figure 2:
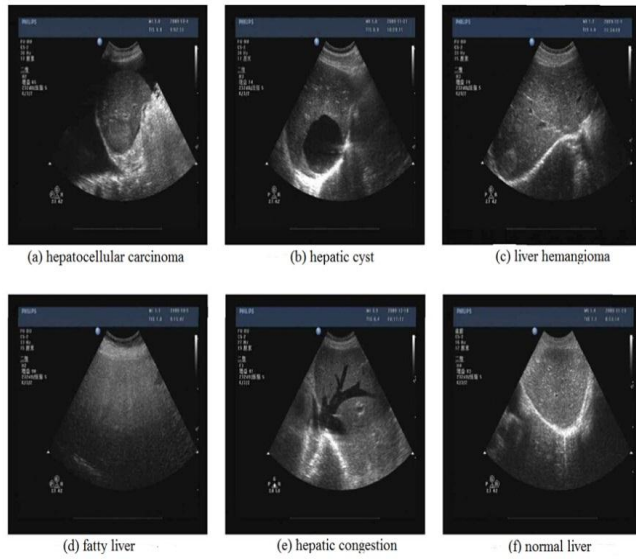

Figure 2.   Six Types of Liver B-Ultrasonic Images

There are differences of different types of liver in Ultrasonic pulse reflection, Attenuation and absorption, so their B Ultrasonic images will have different performance in color, texture and shape, which reflects the pathology of the liver tissue.

B. Feature Extraction

(1) Color feature

The color feature of the image is visually intuitive, and its extraction has robust for any deformations of image translation, rotation, noise and even quality. The color moment method proposed by Stricker and Orengo considers that color information is concentrated in the low-end torque, and first moment (mean), second moment (variance) and third moment (slope) of each color component can effectively express the color distribution in an image. Color moments has the advantage of low character dimensions, and don't need color space quantization, so that can avoid the quantization effect on similarity discriminant.

Note $H(x_i)$ as Gray value of pixel i in the image X, then its third-order color central moments are respectively as Formula (1) ~ (3):

a) First moment: 错误!未找到引用源。   (1)

b) Second moment: 错误!未找到引用源。   (2)

c) Third moment: 错误!未找到引用源。   (3)

The color moment features of six types of B ultrasound images are shown in Table 1:

Table 1. Color Moment Features

	First moment	Second moment	Third moment
hepatocellular carcinoma	50.7218	47.2718	55.1747
hepatic cyst	44.8219	43.8019	56.2819
liver hemangioma	46.0192	38.1238	45.1204
fatty liver	43.1910	31.4911	33.7757
hepatic congestion	53.9128	42.4226	46.2815
normal liver	54.4902	45.4122	51.8418

From Table 1, we can see that in different moment, the color moment feature of normal liver and hepatocellular carcinoma is small; while there are significant differences between color moment feature of fatty liver and that of other types.

(2) Texture feature

Texture is an important feature to depict the space distribution of pixels' neighborhood gray in the image. It is generally defined as some local properties of the image, or a measure of the relationship between pixels in a local region.

We use gray level co-occurrence matrix (GLCM) method to accomplish texture feature

extraction. GLCM not only contains gray statistic information, but also reflects the spatial information of gray distribution. Suppose the image has K gray levels, then the size of GLCM is K × K. The space information refers to the frequency of a pair of pixels with certain distance and direction in GLCM. There are four typical directions: θ=0°, 45°, 90°, 135°; common distance: d=1 (for θ=0°, 90°), or d=√2 (for θ=45°, 135°). For a K×K GLCM, its matrix element is equal to the quantity sum of all pixels that distance is *d* and horizontal angle is *θ*.

Defined elements of normalized GLCM C (d, θ) as Formula (4):

错误!未找到引用源。 (4)

Size of GLCM depends on image total gray series. Haralick proposed 14 parameters based on normalized GLCM to describe the image texture feature. Among them, there are five typical parameters: angular second moment, inertia, inverse difference moment, entropy and correlation. Their calculation formula is shown as Formula (5) ~ (9):

a) Angular second moment: 错误!未找到引用源。 (5)

b) Inertia: 错误!未找到引用源。 (6)

c) Inverse difference moment: 错误!未找到引用源。 (7)

d) Entropy: 错误!未找到引用源。 (8)

e) Correlation: 错误!未找到引用源。 9)

We set distance d=1 (for θ=0°, 90°), d=√2 (for θ=45°, 135°). 错误!未找到引用源。 and D_t is respectively mean and variance of the five basic parameters. Based on GLCM texture features, the value of the five parameters is shown in Table 2:

Table 2. Texture Features Based on GLCM

	Hepatocellular carcinoma	Hepatic Cyst	Liver hemangioma	Fatty Liver	Hepatic congestion	Normal liver
$\bar{t}_1$	30.4118	23.7818	25.9818	14.2648	25.8239	37.2199
$\bar{t}_2$	1.28794	1.28599	1.30841	1.43910	1.25812	1.29581
$\bar{t}_3$	4.02818	3.86221	4.20294	3.86471	4.17940	4.18284
$\bar{t}_4$	0.00157482	0.00258521	0.0024845	0.00389491	0.00200194	0.00181024
$\bar{t}_5$	0.148284	0.104859	0.091548	0.10284	0.080943	0.098592
D_{t1}	230.264	125.284	188.598	40.8591	172.093	289.488
D_{t2}	0.370952	0.369591	0.355271	0.400929	0.322841	0.318548
D_{t3}	2.00127	1.81048	2.18416	1.59827	2.23857	2.04719
D_{t4}	9.4892e-006	2.5429e-005	2.3152e-005	5.0485e-005	1.6284e-005	1.1058e-005
D_{t5}	0.502834	0.402585	0.395872	0.405883	0.408525	0.438582

From Table 2, it is obvious that overall gray distribution of fatty liver is the most uniform, while that of hepatocellular carcinoma and normal liver is opponent; texture change of hepatic congestion is of regulation.

(3) Shape feature

Shape feature is one of the essential features of images, usually associated with the target of the image. The correspondingly characterization methods mainly include two categories: one is edge features, and another is regional features.

For digital image function *f(x, y)*, normalized second-order and third-order central moments can deduce seven invariant moments, as shown as Formula (10) ~ (16):

错误!未找到引用源。 (10)

错误!未找到引用源。 (11)

错误!未找到引用源。 (12)

错误!未找到引用源。 (13)

错误!未找到引用源。 (14)

错误!未找到引用源。 (15)
错误!未找到引用源。 (16)

Extract the invariant features of six types of liver B-Ultrasound images, as shown in Table 3:

Table 3. Invariant Moment Features

	Hepatocellular carcinoma	Hepatic Cyst	Liver hemangioma	Fatty Liver	Hepatic congestion	Normal liver
T_1	0.0134881	0.0150298	0.0131849	0.0136028	0.0140249	0.0098744
T_2	0.00014859	000011858	0.00011084	0.00011357	0.000129428	7.5928e-005
T_3	2.00481e-006	1.40284e-006	1.10274e-006	1.3028e-006	1.5373e-006	6.7824e-007
T_4	3.3728e-006	3.4182e-006	2.5623e-006	3.0224e-006	2.7942e-006	1.3982e-006
T_5	8.9274e-012	7.3573e-012	3.9762e-012	6.4313e-012	5.9271e-012	1.4022e-012
T_6	-1.6028e-009	-6.92723e-009	-2.9841e-009	3.0945e-009	-4.3942e-009	-3.3940e-010
T_7	-8.8247e-012	-4.2249e-012	-3.6904e-012	-6.744e-012	-4.3928e-012	-3.087e-010
θ	4.68724	0.37859	-0.51724	-0.19845	-0.48957	-3.48801
ε	0.73824	0.59847	0.65821	0.64829	0.68767	0.65838

From Table 3, we can see that, the differences of moment features between normal liver and other liver images is significant, while the distributions of the different moments feature of every category change very little.

III. CONCLUSIONS

With the continuous development of computer technology, image processing and pattern recognition technology, feature-level image fusion technology is becoming a hot topic. However, currently its theoretical system and results evaluation system are not yet perfect, and most of the technical and theoretical methods are not universal.

In this article, we take six types of B ultrasound liver images as the research objects, and with multi-feature fusion technology and its application in medical image recognition, made in-depth study on feature extraction issues. Since a single feature is not well represent the medical image information, we research on the extraction method of medical images color, texture and shape features, by color moment features method, GLCM method and invariant moment feature method, an eventually apply them in feature fusion.

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