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MRI Abdominal Organ Tissue Identification using Statistical Distance in Color Space

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Abstract

Magnetic resonance imaging (MRI) is a powerful medical imaging technique to provide detailed images of soft abdomen organ tissues. An automatic organ tissue identification algorithm is useful for physicians to perform initial reading and interpret MRI images. The algorithm presented in the paper uses the distance in color space between centers of organ tissues to identify abdominal organs in MRI images. Experimental results show the algorithm is effective in the RGB, LAB and AB color spaces.

Key words: organ identification, MRI, image processing.

1. Introduction

Magnetic resonance imaging (MRI) is a powerful medical imaging technique to provide detailed images of soft abdomen organ tissues. Manual organ tissue identification by medical dosimetrist is time consuming. To become a dosimetrist requires special training. Hence, developing an automatic organ tissue identification algorithm is useful for physicians to perform initial reading and interpret MRI images.

Segmentation and identification of abdominal organs, such as kidney, liver, spleen, pancreas and stomach, from CT and MRI images, has been attracting a fair amount of research. Lee et al. [1] use a neural network that takes advantage of shape analysis, image contextual constraint, and between-slice relationship to extract disconnected regions from CT images. Fujimoto et al. [2] extract and recognize abdominal organs from CT images using 3D mathematical morphology. To overcome the problem of intensity inhomogeneity in MRI images, the parametric method for bias field estimation is used by Li et al. [3] The fuzzy version of k-means clustering (fuzzy c-means, FCM) is widely adopted for vector quantization and data compression [4][5].

This work uses color fusion MRI methodology to extract color images from longitudinal relaxation time T_1 and transverse relaxation time T_2 images. A previously established standardized acquisition and image processing protocol is used to produce color MRI images of a variety of abdominal tissues of human subjects. We assume that pixels for each tissue object in an MRI image have similar property, whilst pixels in different organ tissues are different in color space. Therefore, identifying an organ tissue in an MRI image becomes the problem of finding the closest set of pixels of a known tissue in the color space.

In this work, abdominal MRI images are first segmented using fuzzy c-means clustering in the $l*a*b$ color space [5]. A physician can choose a region of interest of an unknown abdominal organ in the segmented image. Statistical distances between the centers of known abdominal organ tissues and the region of interest of an unknown organ are used to identify which organ it belongs to. T-test is performed to further verify the results. Experiments show that the algorithm yields very satisfactory results. Results obtained from data in various color spaces are explored as well.

The remainder of the paper is as follows. Section 2 describes the statistical distance-based organ identification algorithm. Section 3 discusses the experimental data preparation and results. Section 4 concludes the paper with an outline for future work.

2. Statistical Distance-based Organ Identification

The different organs or tissues have different combinations of biophysical parameters that are mapped in MR images. When each of the parameter maps are assigned color masks and then fused into a single full color image, tissues with different biophysical parameters are displayed as different in color. Tissues with very similar biophysical parameters appear as very similar in color.

We assume that color is a constant property for each tissue object in an MRI image. Therefore identifying organ in an abdominal MRI image becomes the problem of finding the shortest distance between the center of a known abdominal organ tissues and the region of interest of the unknown organ.

The algorithm is designed to identify different organs from an MRI image based on the color center of that image. The color center of a region of interest is defined as follows:

$$C_j = \frac{1}{n}\sum_{i=1}^{n} i_j \qquad (2.1)$$

where C_j represents the center of color channel j (for example red, green or blue in RGB space) and n is the number of pixels in the region.

The distance for each pixel from the center of color channel C_j is calculated as follows

$$d_i = \sqrt{\sum_{j=1}^{m} (i_j - C_j)^2} \qquad (2.2)$$

where d_i is the Euclidian distance from center of the color space for pixel i and m is the number of channels in the color space. The mean of the distances is then calculated as follows

$$\bar{d} = \frac{1}{n}\sum_{i=1}^{n} d_i \qquad (2.3)$$

where n is the number of pixels in the region of interest. And then the standard deviation σ is calculated as shown here

$$\sigma = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(d_i - \bar{d})^2} \qquad (2.4)$$

This process is repeated for all the sets up images representing different organs.

After an unknown organ in an image, represented as u, is selected the probable organ identity is determined through the following process. The center of the color space C_u and the number of pixels in the image n are found as they were in the predefined data. Then it iterates through the following process for each known organ k. It starts by calculating the Euclidian distance between the center for the unknown image region and the center for known organ k.

$$d_{uk} = \sqrt{\sum_{j=1}^{m}(C_{uj} - C_{kj})^2} \qquad (2.5)$$

m represents the number of color channels in the image. d_{uk} represents the distance between the centers of unknown image region u and known organ k. This distance is then converted into a t-score using the following equation

$$t_{uk} = \frac{d_{uk}}{\sigma_k / \sqrt{n}} \qquad (2.6)$$

where t_{uk} represents the t-score for image region u compared to known organ k.

Basing the identity of the image region solely upon its distance from the organs color center can cause problems. In the graph below [6] notice that the center of the image, represented by the red line, is closer to organ B yet according to the frequency diagram the prospect of the organ adhering to organ A is more likely.

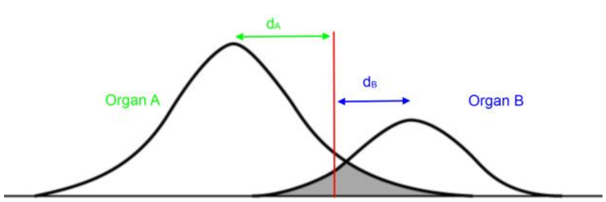

Fig 2.1 Centers of Organ Image and Color Distributions

Using t-distribution takes this problem into account by defining the distance in terms of how many standard deviations it is away from the organ.

3. Experimental Results

Images used in experiment are extracted from longitudinal relaxation time T_1 and transverse relaxation time T_2 MRI images. The ColorMRI[tm] methodology generates full color images from the plurality of gray tone images acquired by magnetic resonance imaging. The gray tone images are essentially mappings of biophysical/nuclear magnetic resonance parameters such as longitudinal relaxation time T_1, transverse relaxation time T_2, proton density (PD), magnetic susceptibility, gadolinium contrast media enhancement, etc. Assignment of color masks to each biophysical parameter image and subsequent fusion of the color masked images results in a full color image in which the unique color of each pixel in the RGB color space represents the combination of unique biophysical parameters of the tissue represented by that pixel.

Following is an example of an abdominal color MRI of labeled regions of interest. Liver, pancreas and kidney are labeled. Hepatic tissue (liver) is located on the far left side of the image. Renal tissue is found adjacent to the liver. Pancreatic tissue is located toward the center of the image.

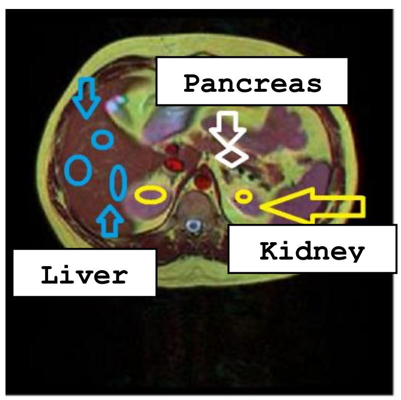

Fig. 3.1 An Abdominal Color MRI of Labeled Region of Interest

In the experiments, MRI images are separated into two groups. The training data set contains 80% of the whole set. The rest 20% are for the testing data set. From both the training and testing data set, images are first segmented using fuzz c-means clustering described in [5]. The regions of interest (ROI) of various abdominal organs are manually selected. The center of each ROI is calculated using equation (2.1). The mean value of distance between the ROI of an unknown organ and every known organ is obtained using equation (2.3). We use equation (2.5) to calculate the t-score for ROI of an unknown orgran compared to a known organ. A low t-score indicates fewer standard deviations from the center therefore the organ with the lowest t-score is determined to be the identity of the image.

Table 3.1 shows the centers and standard deviations of organs in the training data set in the RBG, LAB and AB color space respectively.

Name of Organ	Centers in RGB	Centers in LAB	Centers in AB	Standard Deviation in RGB	Standard Deviation in LAB	Standard Deviation in AB
Kidney	[114,87,114]	[104,143,117]	[143, 117]	6.63	3.77	3.51
Liver	[97,53,49]	[71, 147, 140]	[147, 140]	6.05	3.59	2.01
Muscle	[78,31,41]	[49, 151, 132]	[151, 132]	8.94	5.49	2.45
Pancreas	[107, 66, 59]	[83, 146, 140]	[146, 140]	8.7	5.23	1.5
Spleen	[114, 71, 94]	[91, 150, 122]	[150, 122]	4.68	2.8	1.68
Stomach	[143,174,213]	[178,124,104]	[124, 104]	10.19	5.3	4.49

Table 3.1 Centers and Standard Deviations of Known Organs of Training Data in RGB, LAB and AB Color Space

Accuracy (%)	**Kidney**	**Liver**	**Muscle**	**Pancreas**	**Spleen**	**Stomach**
In RGB	100	100	100	100	100	100
In LAB	100	100	100	100	100	100
In AB	100	100	67	75	100	100
Using t-score in RGB	100	100	100	100	100	100
Using t-score in LAB	100	100	100	100	100	100
Using t-score in AB	67	100	100	25	100	100

Table 3.2 Organ/Tissue Identification Results

Results of organ identification are listed in Table 3.2. It is demonstrated that the statistical distance-based identification algorithm yields very satisfactory results in both the RGB and LAB color spaces. The behavior of the algorithm in the AB space deserves a discussion.

In the RGB color space, differences among colors perceived by the human eye as being of the same entity are not mirrored by similar distances between the points representing those colors in the color spaces. The problem is reduced in the CIE LAB color space [7]. In the CIE LAB space, L represents the brightness, i.e. intensity. From the results shown in Table 3.2, it is noted that color intensities play an important role in distinguishing tissues.

Organ Name	**Distance in RGB Space**	**Distance in LAB Space**	**Distance in AB Space**
Kidney	61.6	31.9	25.7
Liver	20.1	13.8	**2.9**
Muscle	49.9	37.1	11.0
Pancreas	**5.2**	**3.4**	3.2
Spleen	38.9	21.7	20.6
Stomach	193.6	103.5	44.5

Table 3.3 Distances of a ROI of Pancreas from Other Organs

In our experiments, ROIs of pancreas are mis-identified as liver tissue in the AB space. Table 3.3 shows the distances of it from known organs. This is due to the histological differences between the two organs even though both are glandular organs. Hepatic tissue has a more extensive blood supply than the pancreas, allowing it to store iron, synthesize proteins, and house many mitochondria that contain cytochrome c. The presence of ferritin and cytochrome c has an effect on the imaging of the liver in that it lowers the signal of the waves that are recorded by the MRI scanner. This is evidenced by the brightness values of liver and pancreas listed in Table 3.1. Liver and pancreas tissue brightness values in the LAB space are 71 and 83 respectively. In the mean time, their AB components are similar, $[147,140]$ and [$[146,140]$ for liver and pancreas respectively.

4. Conclusions

In this paper, we use the statistical distance-based algorithm to identify abdominal organ in MRI images. Experimental results show that distance between centers of regions of interest of organ tissues can effectively distinguish tissues. Developing an automatic organ tissue identification algorithm is useful for physicians to perform initial reading and interpret MRI images. In the future, the algorithm will be further tested on more MRI data, and will be extended to identify other human tissues.

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