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Experiments with automatic segmentation of liver parenchym using texture description

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***Abstract*—This paper provides summary of our experiments with automatic segmentation of liver parenchym. It presents methods and classifiers that we used on computer tomography medicine data. In introduction there are a description of our motivation to do this research. Second part contains information about our approach, list of methods and classifiers. In part called results, we presents figure with subset of our experiments and described evaluation. Summary at the end of this paper presents future research of this topic.**

***Keywords*—liver parenchym, computer tomography, texture description, texture analysis**

I. Introduction

COLORECTAL Carcynoma (CRC), also known as cancer of the gastrointestinal tract, is one of the most frequently diagnosted malignant tumour in the Western world. There are many factors causing CRC. Particularly life style and alimentation habits (alcohol, fried and grilled food etc.). Other factors are heredity and enviroment conditions. In many cases, CRC is often acompanied by metastasis in liver parenchym. If metastasis are resectable, the surgeon will do resection of liver tissue.

Before operation, its necessary to use modern imaging methods to judge, if it is possible to remove damaged liver tissue. The most common imaging technique is computer tomography (CT). In special cases it is followed by magnetic resonance (MRI). During operation, surgeon cuts out relatively big part of the liver parenchym. It is important to preserve function of the remaining part of patient liver. Statistics show that there are 25-40% of people who outlive longer than 5 years after resection and 20% of people who survive longer than 10 years after operation. Thanks to modern operating techniques, the postoperative mortality decreased from 15% to only 5% of patients.

As we mentioned in previous paragraph, it is necessary to do preoperative CT examination of liver parenchym. The next important step is marking liver area in CT data in order to compute volume of the liver and both parts after resection. There are some ratio of volume of healthy part of liver tissue to patient weight. The most common technique of marking liver in CT data is highlighting contours of liver slide by slide. This marking process is really time-consuming. It takes approximately 30 minutes. The question is, it is possible to do it automaticaly and significantly faster using computer?

Indications of dealing with this task are described in various papers. As in other scientific branches, there is a problem with comparing of different approaches to automatic marking of liver tissue. Within 3D Segmentation in the Clinic : A Grand Challenge there arised competition SLIVER07 and comparsion metodology to our task. Results of this competition is in [2]. Summary description of different approaches is in papers [4] and [1]. One of the most sucessful method is described in [3]. Paper [5] describes method which is based on segmentation of portal vein. Nowadays (2014) that method has the best score in SLIVER07. The dataset contains CT data and ground truth data (manually segmented) that can be used for evaluation.

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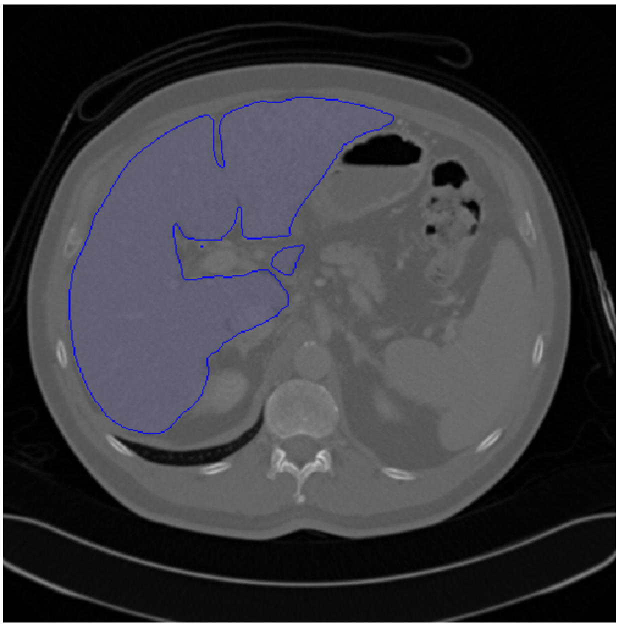

Fig. 1. Example of SLIVER07 computer tomography data. Blue region is manually segmented liver parenchym - i.e. ground truth for our experiments

II. Methods and Classifiers

We tried couple well known texture description methods. Our approach contains of data decomposition on smaller tiles. Tile is a $X \times Y \times S$ block, where X is width of tile, Y is height and S is number of data slices. We applied methods on them in order to get local description of the tile. This approach had some advantages and few disadvantages. The advantage is that it is easy to implementation. Disadvantage on the other hand is unknown ideal size of the tile. Too small tile is bad because of small amount of information and large tile is bad because the information hasnt local character. Unfortunately, estimation of tile size is not simple task. Below, there are list of texture description methods which we used.

Each CT data in our dataset has different size of voxels. To suppress this issue a normalization algorithm was used. It is based on resampling input data to same voxel size. We used 1 mm for each axis.

A. Texture descriptors

1) Histogram method: Simplest method of our approach. It creates histogram directly from data tile. Generated histogram is whole description of texture in local area which is defined by size of the tile.

2) Gabor filters: Principle of this method is creation of bank of 2D filters with different orientation. The core of Gabor filter is assembled of Gaussian function and modulated by sin function. Result is created as convolution of source data and filter itself. Each response contains information about occurence of wave with specific frequency omega and orientation sigma.

3) Gray Level Co-occurence Matrix (GLCM): Co-occurence matrix is square matrix of size NxN where N is number of gray levels. On the position [i,j] is information about number of co-occurence between gray level i and gray level j. There are also defined maximum distance of co-occurence and angle in which the method searches co-occurences.

$$\mathbf{Img} = \begin{bmatrix} 0 & 2 & 1 \\ 1 & 1 & 0 \\ 0 & 2 & 0 \end{bmatrix} \Rightarrow \mathbf{P}(0,1) = \begin{bmatrix} 0 & 1 & 3 \\ 1 & 2 & 1 \\ 3 & 1 & 0 \end{bmatrix}$$

where $\mathbf{Img}$ is source data and $\mathbf{P}(0,1)$ is co-occurence matrix for angle 0 and distance 1.

4) Local Binary Patterns (LBP): Local Binary pattern method transforms all values in neighbourhood of center pixel to one binary number. That number defines texture of whole local area. Approach is shown on the example:

$$\mathbf{G} = \begin{bmatrix} g_1 & g_2 & g_3 \\ g_8 & g_0 & g_4 \\ g_7 & g_6 & g_5 \end{bmatrix} \Rightarrow \begin{bmatrix} 0 & 3 & 1 \\ 7 & 2 & 1 \\ 9 & 1 & 4 \end{bmatrix} \Rightarrow$$

$$\sum_{i=1}^{n} sg(g_i - g_0) \cdot 2^{n-1} \Rightarrow b = [11010010] \Rightarrow 210,$$

where sg is 1 if $g_i < g_0$ and 0 otherwise, n is number of pixels g_i in neighbourhood of center pixel g_0.

At the end we get LBP numbers for all local neighbourhoods in tile. We are able to create histogram that contains all information about texture of the tile. There are a lot of improvements of LBP method, but we used basic algorithm we dont have to deal with rotation in CT data.

Histogram method and LBP are neighbourhood independent methods. i.e. It is possible to use them on N-dimensional data. On the other hand, the GLCM and gabor filters can be used only on 2-dimensional data - i.e it is necessarz to do decomposition of tile to slices.

We implemented histogram features and LBP (based on [7]). Scikits-image implementation of GLCM and Gabor Filters was used [6].

B. Classifiers

In our experiments we worked with seven different classifiers. Naive Bayes, Support Vector Machine (SVM), Gaussian Mixture Model (GMM), Decision Trees (DT), Random Forest, Quadratic discriminant analysis (QDA) and Linear discriminant analysis (LDA). Python module Scikits-learn implementation of these algorithms was used. Results

III. Experiments

Our experiments are composed of three parts. In first step, the appliaction loads first half of SLIVER07 dataset and makes smaller tiles. In second part, script applied one (or more) of texture description methods on each tile and trains one of classifiers listed above. Ground truth from dataset is used as supervisor information that decides whether pixel belongs to liver or to non-liver region. Third part consist of applying method on test data and classifying acquired result.

After classification we have marked each pixel by number 1 or 0. Number 1 is pixel classified as liver and 0 is non-liver pixel. The accuracy of our experiments is limited by siye of the tile. The best scenario would be tile of size $1 \times 1 \times 1$. Unfortunately, it is impossible to applied texture description methods on the single pixel. This is the reason, why we never get absolutely accurate results.

Fig. 2. LIver Surgery Analyser (Lisa). Software package developed by M. Jiřík et al. We used Lisa to our experiments.

IV. Results

As we mentioned in previous section, we did set of segmentation experiments of liver tissue. We combined texture description methods with classifiers. For our experiments we used Sliver07 training dataset. One half of twenty CT images was used for training classifier with texture descriptor. After that, remaining data was used for evaluating experiment.

Evaluation is based on five diferent metrics: Volumetric overlap error (in percent), Relative absolute volume difference (in percent), Average symmetric surface distance (in milimeters), Root Mean Square symmetruc surface distance (in milimeters) and Maximum symetric surface distance (in milimeters). These metric are rescaled to score from 0 (negative values are aligned to zero) to 100. Total score is the average of the individual scores. Complete description of methodology can be found in [2].

In the figure 3 you can see scores of individual combinations of descriptor and classifier. From total of 44 experiments a subset with significant score is selected.

We used acronyms to describe each combination of method and classifier. First part of acronym is the label of method: fh - feature histogram, glcm - gray level co-ocurence matrix, gb - gabor filter and lbp - local binary patterns. In some cases there are multiple methods used. The second part is the label of classifier: dt - decision tree, g - naive Bayes classifier and lda - LDA. Last part of acronym is the information about voxel size normalization. Column marked as h+glcm_dt_n has the best performance. Feature vector is a combination of histogram method and gray level co-ocurence matrix. As classifier we used decision tree classifier in this case.

Generally the decision tree classifier was better than other classifiers used in our experiments. The LDA classifier had good results too. On the other side of score table were SVM and naive Bayes classifier, which had very poor results.

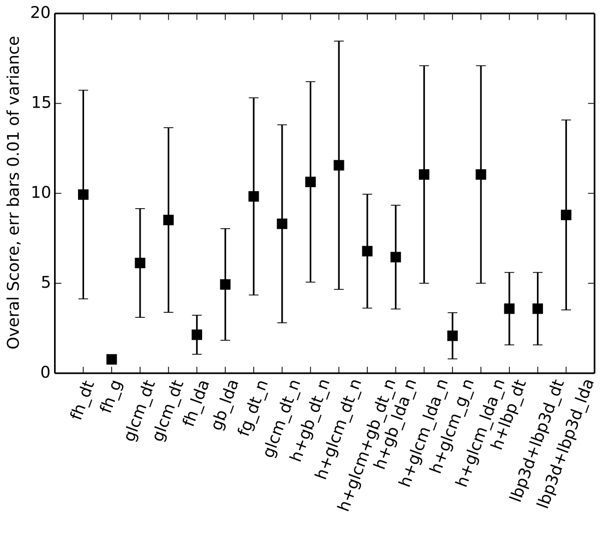

Fig. 3. Subset of experimental results. Acronyms are described below.

V. Conclusion

As you can see in previous section, results are dependent on texture description method, classifier and amount of noise in processed data. Because of that, there are big difference between various combinations. Texture description itself is not the best way to classify tiles in noisy CT data.

There are a lot of opportunities to improve results by trying new combinations of descriptor and classifier, trying different type of tiles - i.e. overlapping tiles - or adding some kind of support information about processed data.

Other approach in this task might be description vector created by some feature detection method as SIFT, SURF, etc. instead of texture descriptor. Neural network classification could be interesting to. We want to try several ways in our future research of this topic.

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