ISSN 2229-5518

AUTOMATIC SEGMENTATION OF LIVER IN CT IMAGES

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Abstract — Now-a-days accurate way of measuring liver is essential for segmentation. Several efforts have been designed for acquiring liver segmentation procedures in the field of medical image processing. Although some intelligent segmentation procedures have been designed, their own performances are still challenged by the poor image contrast. Medical image segmentation performs significant role in image processing technique. Segmentation is generally a part of image analysis which means that a part of partitioning an image into multiple segments or extracting the region from the whole image. Image segmentation is usually to cluster pixels into salient image regions. Within this report, the notion of involving, Auto-context Product (ACM) is employed to segment the liver from CT images. Auto-context model will be performed iteratively to develop a sequence of classifiers by means of integrating both image appearance and along with context features in the local patch. Specifically, Auto-context model (ACM) and multiple sequences of ACM-based classifier are generally constructed, respectively in each atlas space during the training stage. Thus in the testing stage, a new image will be segmented by applying the sequence of learned classifier of each atlas and fusing multiple segmentation results from multiple atlas. Finally, the ACM method is applied to segment the liver and in addition to reduce the average volume overlap error and achieve more accuracy and efficiency.

Index Terms — Liver segmentation, ACM, Multi atlases, Mean Shift Technique, SSM, PCA, GLCM, CT.

1 INTRODUCTION

Now-a-days, the medical image segmentation attracts progressively more and more attention and interest. It provides, routinely, to delimit the internal structure on the patient.

The medical imaging will probably be employed to detect and as well as visualize the internal structures. These structures usually do not appear in a single image, however it requires several acquisitions. The application of image analysis is continuously expanding through all areas associated of science, industry, including Medicine such as detecting cancer with in MRI, CT, and PET. Computed Tomography (CT) is often a medical imaging method using tomography.

Segmentation can be an important process throughout in medical image analysis as well as classification especially for radiological evaluate as well as computer-aided analysis. The goal of segmentation should be simplify or modify the actual representation of an image into something which is actually much more significant and also much better to analyse. Segmentation can be performed manually, automatically or semi-automatically. The manual segmentation is time consuming and it provides more accuracy and reliability.

The purpose of automatic segmentation of the liver is an indispensable anticipated outcome of examining the liver function which enables it to aid in diagnosis regarding liver ailments. The primary difficulty in automatic liver segmentation through contrast-enhanced CT data whose high intensity of liver tissue is usually similar to just like surrounding entities including belly, pancreas, kidney as well as muscular tissues.

Until now, different segmentation procedures are created pertaining to liver segmentation from CT images for instance those based on statistical shape model, graph cut, region growing, and threshold based methods and learning based methods.

A graph cut could be the process of partitioning some sort of directed or perhaps undirected graph into disjoint sets. The image is treated as a graph - each pixel is a graph node. The particular concept of optimality regarding these kinds of cuts is usually introduced by associating an energy to every single slice. Complications of the type are studied within the field of graph theory but can for graphs with more than only a few nodes be notoriously difficult. Even so, from the time that that grew to be noticeable that numerous low-level perspective problems can be presented as finding energy minimizing cuts in graph these types of approaches have obtained lots of attention with this personal computer perspective vision community. Graph cut strategies are successfully applied to image restoration, texture synthesis as well as impression segmentation. Drawback in the graph-based methods is that they are definitely not very easily extended to multi-label task and some other is that they are not to adaptable.

ISSN 2229-5518

The easiest way of image segmentation is named the thresholding method. Thresholding is probably the most crucial strategies to image segmentation. In this method, pixels that are likewise in grayscale (or another feature) are grouped with each other. The segmentation depends upon image property getting threshold and also on how the threshold will be selected. Threshold based segmentation is needed to separate one or more desired objects from other background. In most sensible conditions the simple thresholding is unable to segment objects of interest.

Region growing can be a uncomplicated region-based image segmentation approach. It is usually categorized as a pixel-based image segmentation approach, since it consists of the selection of initial seed points. This process of segmentation investigates the actual nearby pixels regarding the initial seed points and determines whether the neighboring pixels can be added to the region. The regions tend to be after that expanded from these seed points to adjacent points based on a region membership criterion.

Statistical Shape Model can be used to gauge the shape variation associated with diverse internal organs along with examining the accuracy and reliability associated with both normal and abnormal data. SSM-based segmentation approaches work with Principle component Analysis (PCA) to capture and estimate the shape features of the liver. The actual development associated with landmark construction corresponding to all training datasets can be step one in the majority of SSM based liver segmentation, which involves the industry challenging along with difficult undertaking. Major negative aspect in this model is complicated to classify the abnormal liver. From the earlier period associated with sickness, the abnormal liver may not go through very significant morphological adjustments as compared to normal liver, complicated to classify abnormal data.

Principal Component analysis is employed to identify the pattern in data. It is used to emphasize the correlated and uncorrelated patterns of data. Considering that the pattern within data can be difficult to find within the data of high dimension, PCA is just not better to symbolize the shape with liver.

Recently, several efforts are actually made to accomplish for liver segmentation methods. ACM (Auto-Context Model) continues to be offered to segment the liver automatically from CT images. However, ACM combines image physical appearance with the context feature information through learning the sequence of classifiers, which in turn eliminates the complicated method to make a specific SSM model and segment the liver automatically.

To segment the liver on a new image, all atlases along their respective classifier learned in the training stage, will be first transformed onto the new image by a registration technique. Each point in the new image will be classified by the respective classifier of each atlas and its final segmentation result will be obtained by fusing all result from all atlas.

2 METHODS

There has been many medical segmentation algorithm produced in this beyond. They have already produced encouraging results, although there are numerous common drawbacks. With this area, the detail work of Auto-context style will be mentioned. Auto context model has the main benefit of fusing image appearance and context features without necessity of shape representation.

2.1. Learn ACM classifier in each Atlas

With regards to our method, is mainly good learning based liver segmentation algorithm is to accurately label each point. In training stage M images and also corresponding manual liver label are considered as when $i = y \varepsilon \Omega$, $i = 1, \ldots, M$ and $T = L_i(y)$ are equally consider as an atlas I_i that may be $A = A_i = (I_i, L_i)$ $i = 1 \ldots M$ for training the ACM classifier. Training image is usually dealt with just as one atlas to build sequence of classifier. In the training stage, all atlases usually are ought to aligned which is often attained through affine registration regarding manually-segmented liver within L_i and L_j. Pertaining to Atlas I_i, the classifier regarding liver segmentation are going to be trained not just using the current atlas $A_i = (I_i, L_i)$ and also their aligned atlas (M-1). Within the training period, ACM classifier will be trained by incorporating image appearance and context feature, thereby building a sequence classifier. Eventually, M sequence of classifiers is attained for each and every atlas A_i $(i = 1) \ldots M$. Within the testing stage, the test image is going to be aligned about every atlas space after which it is segmented with the sequence involving ACM classifier.

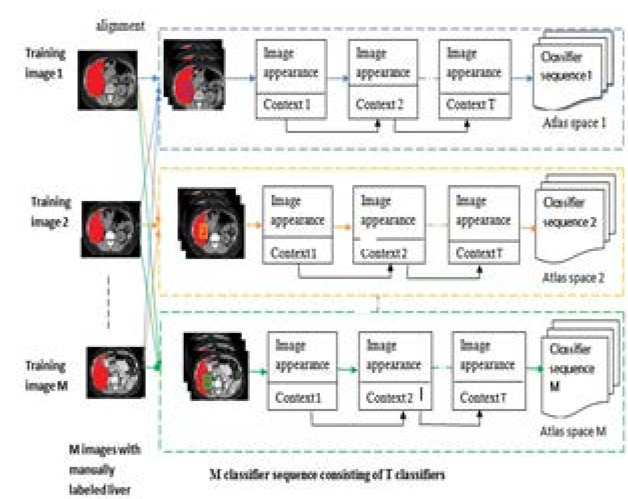


Fig 1.Training Procedure of ACM

2.2 ACM based classifier Training

During training, consider S as training set

$$s = \{({}^{a}y_{ji}, {}^{a}X_{j}(N_i)),\ j = 1...m, i = 1...n\} \dashrightarrow \quad (1)$$

Where m is the number of training images, n is the number of pixels in each image ${}^{b}y_{ji}$ for pixel i in image ${}^{a}X_j$ and ${}^{a}X_j(N_i)$ denotes the local image patch centered at pixel i in image ${}^{a}X_j$. ACM is carried out inside the space of each one atlas I_i to train the sequence of classifier from atlas I_i along with other aligned atlas I_j. Each of the atlases are ought to aligned which is often accomplished by simply affine registration. The first classification map may be computed on atlas A_i in addition to all the aligned atlases A_j, by performing union on those aligned liver label maps of all atlases,(i.e., $L_i \cup \{\cup_{j=1 j\neq i}^{M} L_j\}$).

Fig 2. Manual Labeling

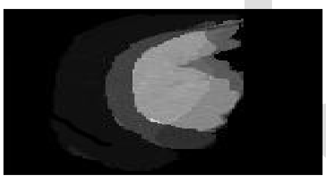
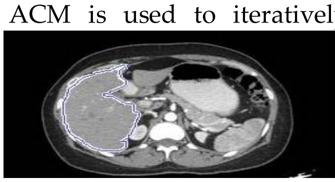


Fig 3. Atlas Formation

Then, ACM is used to iteratively find the optimal classifiers by repeating the following steps up to T iteration.



First classifier is learned based on the image appearance and context feature. The context features are obtained from the classification maps obtained from the classifier. For each training image ${}^{b}X_j$, the classification maps C_j are computed by the learned classifier. Algorithm for the new training set

$$s' = \{({}^{a}y_{ji}, ({}^{a}X_{j}(N_i), C_j(i))),\ j = 1...m, i = 1...n\} \dashrightarrow \quad (2)$$

where $C_j(i)$ is the classification maps centered at pixel i for image ${}^{a}X_j$. A new classifier is then trained not only based on the image appearance obtained from ${}^{a}X_j(N_i)$ and context feature obtained from $C_j(i)$. First classifier is learned based on the image appearance and classification maps created by the current classifier are used as context information along with image appearance feature to train the new classifier. Final classification map at low resolution will be used as the initialization for the next high resolution. Algorithm iterates until we obtain T classifier sequence. Sequence of learned classifier will be

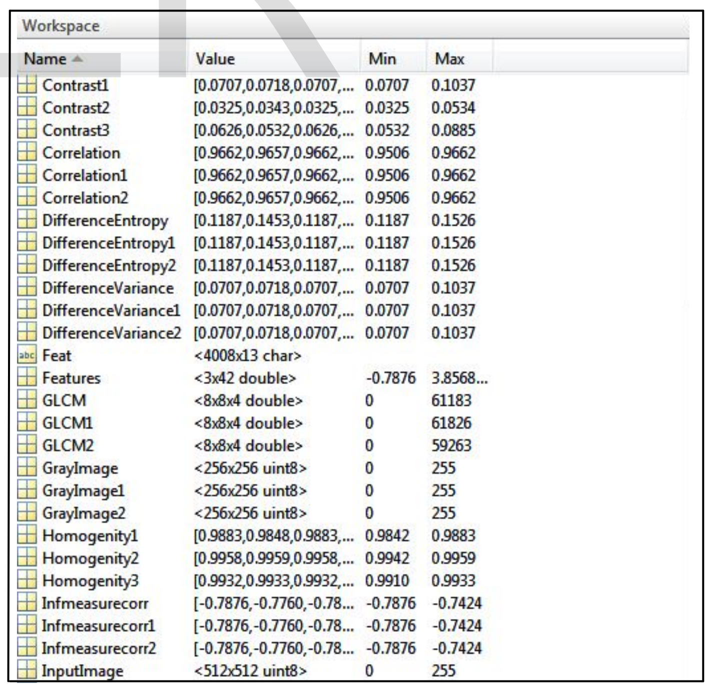
$$C^{(t)}(y_i \mid (X(N_i), C^{(t-1)}(i)), t = 1...T\} \dashrightarrow \quad (3)$$

2.3 Image Appearance

Image physical appearance attribute consists of intensity, spatial location, intensity mean, variance, Haar features and texture information as gray level co-occurrence matrix (GLCM) are expected to be able to determine with every local patch of point which is deemed.

2.4 Gray level co-occurance matrix

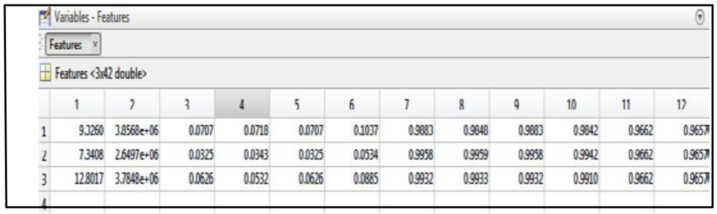
GLCM exemplifies the particular distributions of the intensities along with information about the corresponding positions involving neighboring pixels of an image. It will help to afford the valuable information about the corresponding positions of the neighbouring pixels in an image. Contrast, Energy, Entropy, homogeneity are viewed as being an more additional features in our method and Haar features from different scales. Haar features are a digital image features employed in object identification, can be explained as the particular variation involving the sum pixels involving areas in the rectangle, and this can be from almost any position and scale inside the original image.



Workspace

Name	Value	Min	Max
Contrast1	[0.0707,0.0718,0.0707,...	0.0707	0.1037
Contrast2	[0.0325,0.0343,0.0325,...	0.0325	0.0534
Contrast3	[0.0626,0.0532,0.0626,...	0.0532	0.0885
Correlation	[0.9662,0.9657,0.9662,...	0.9506	0.9662
Correlation1	[0.9662,0.9657,0.9662,...	0.9506	0.9662
Correlation2	[0.9662,0.9657,0.9662,...	0.9506	0.9662
DifferenceEntropy	[0.1187,0.1453,0.1187,...	0.1187	0.1526
DifferenceEntropy1	[0.1187,0.1453,0.1187,...	0.1187	0.1526
DifferenceEntropy2	[0.1187,0.1453,0.1187,...	0.1187	0.1526
DifferenceVariance	[0.0707,0.0718,0.0707,...	0.0707	0.1037
DifferenceVariance1	[0.0707,0.0718,0.0707,...	0.0707	0.1037
DifferenceVariance2	[0.0707,0.0718,0.0707,...	0.0707	0.1037
Feat	<4008x13 char>		
Features	<3x42 double>	-0.7876	3.8568...
GLCM	<8x8x4 double>	0	61183
GLCM1	<8x8x4 double>	0	61826
GLCM2	<8x8x4 double>	0	59263
GrayImage	<256x256 uint8>	0	255
GrayImage1	<256x256 uint8>	0	255
GrayImage2	<256x256 uint8>	0	255
Homogenity1	[0.9883,0.9848,0.9883,...	0.9842	0.9883
Homogenity2	[0.9958,0.9959,0.9958,...	0.9942	0.9959
Homogenity3	[0.9932,0.9933,0.9932,...	0.9910	0.9933
Infmeasurecorr	[-0.7876,-0.7760,-0.78...	-0.7876	-0.7424
Infmeasurecorr1	[-0.7876,-0.7760,-0.78...	-0.7876	-0.7424
Infmeasurecorr2	[-0.7876,-0.7760,-0.78...	-0.7876	-0.7424
InputImage	<512x512 uint8>	0	255

ISSN 2229-5518



	1	2	3	4	5	6	7	8	9	10	11	12
1	9.3260	3.8568e+06	0.0707	0.0718	0.0707	0.1037	0.9883	0.9848	0.9883	0.9842	0.9662	0.9657
2	7.3408	2.6497e+06	0.0325	0.0343	0.0325	0.0534	0.9958	0.9959	0.9958	0.9942	0.9662	0.9657
3	12.8017	3.7848e+06	0.0626	0.0532	0.0626	0.0885	0.9932	0.9933	0.9932	0.9910	0.9662	0.9657
4												

Fig 4. Texture Feature Extraction

2.5 Context Features

The context features are extracted from the classification probability map obtained at the previous iteration, in order to capture global anatomical information around each voxel in the image. In general, the context features are used to describe the spatial configuration of particular point w.r.t. its neighboring points. In contrast to the local appearance and texture features, the context features are extracted from a large region surrounding the current location, rather than its small neighborhood.

Context location are obtained from the current pixel of interest connected along with nearby pixels are stretched out of the current pixel. Specifically, for each point X_n^i, a number of rays in equal-degree intervals are disseminated outward from the center point, and the context locations on these rays are sparsely sampled (rectangular boxes in Fig.4).

For each sampled location, the classification probability on the center point and the average probability within a 3 × 3 neighborhood are used as context features. As shown in Fig. 4, the liver region in the sequential classification maps becomes more and more prominent and the boundary between the liver and background becomes sharper and sharper, as the ACM progresses.

For 2D, context feature are extracted by 8 rays inside 45̊ degree are prolonged out of the current pixels along with we all sparsely small sample the context location on these rays. From all location in the input image within 3 pixels are away from the current pixels are usually in the candidate pool. In the training stage, for every round, the algorithm will probably automatically select on distinct context location both the short range along with extended range. Context feature implicitly represent shape along with configuration information.

1. Update the context feature features in the training set θ^t by using update classification maps $C^{t-1}(X_i)$ and $C^{t-1}(X_j)$ ($j = 1\ldots M, j \neq i$).
2. Train the classifier by Adaboost by automatically selecting and fusing context feature with image appearance.

3. Use the trained classifier to assign the label to each point in I_i and all I_js, thus obtaining $C^t(X_i)$ and $C^t(X_j)$ ($j = 1\ldots M, j \neq i$) for the next iteration $t + 1$.

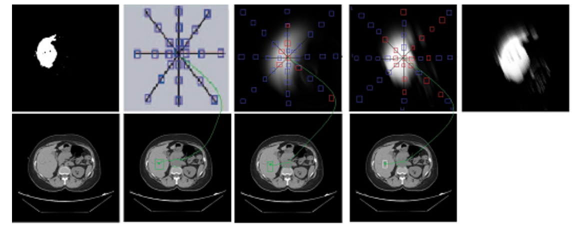


Fig 5. Classification maps

At the conclusion of the training procedure we will obtain M sequence of trained classifier with sequence of having T classifier which corresponds to total m atlases.

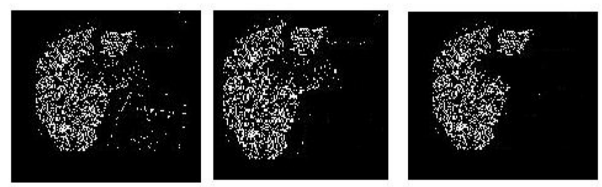


Fig 6. Classifier Sequence

2.6 Multi-atlas based segmentation

In the testing stage, all atlases is going to be registered towards the test image, in order to map the classifier realized from the training stage. The image appearance along with context feature is going to be calculated for every point connected with test image X_{test}. Labeling the test image can be conducted by performing each sequence of classifier of each atlas and by following the training procedure of ACM. All the classification maps are incorporated into a final label result. Classification maps are simply just binarized and the fused together pertaining to producing remaining segmentation result. That basic procedure for segmentation may possibly have an effect on the segmentation reliability in order to overcome this particular negative aspect most of us applies advanced label fusion technique to produce segmentation result more accuracy and reliability.

2.7 Label fusion

Regarding label fusion via a set of possibility atlases, the best technique is usually majority voting which usually presumes that each atlas attributes equally to the image segmentation. Given the actual weighted normal probability map, with the degree on each and every position implying the likelihood of staying liver class in addition to non-liver class, we further additional implement the level set method on this possibility map to discover the final segmentation.

3 Testing stage

ISSN 2229-5518

1) The classifier sequences produced to all atlases will likely be transformed onto the test image.

2) Next, the image appearance in addition to context feature is computed at each and every point with the test image.

3) Final probability maps acquired simply by most atlases are fused to build a fused probability map, in line with the local image similarity relating to the test image in addition to each and every aligned atlas.

4) The final label for test image relies on applying an level set algorithm to obtain the liver.

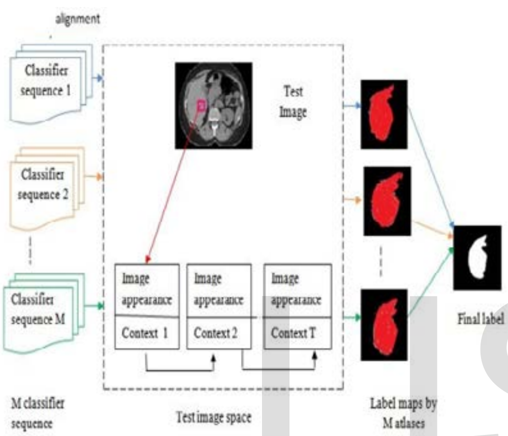


Fig 7. Testing stage

3.1 Mean shift over segmentation

A result of the complexness of encompassing structure like liver tissues plus next to organs(heart and stomach), actual segmentation of liver is critical. In order to take care of this specific worry, the mean shift algorithm is being employed to stay away from leakage of image region might be prevented. It could differentiate the liver tissues on the cardiovascular system.

So that, in order to speedup the particular segmentation, all of us utilize region based labeling it could randomly choose and also execute classification rather than pixel based labeling. Pixel based labeling is not sufficient.

Region based labeling tests an image and also group their pixels into components based on pixel connectivity and all pixels in a connected component share related pixels and intensity values and are somehow connected with each other.

4 CONCLUSION

Therefore, following these discussions and the design review, we can present learning based algorithm method for segmentation of liver more accuracy. By the use of Auto-context model and multi–atlas based segmentation are employed for building sequences of classifiers and further applied for liver segmentation in the new test image and we could able to achieve more accurate result. Most of us consider, our learning-based segmentation method will enable the fully automatic segmentation for the CT images and reduce the average volume overlap error and attain much more better segmentation results.

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