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Automated Liver Tumor Detection Using Markov Random Field Segmentation

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Abstract

Liver cancers are one of the most popular cancers occurring now a days.The majority of liver carcinomas are dueto alcohol related cirrhosis and hepatitis. Also there are metastatic liver cancer,in which cancer originated from other organs extends to liver. Early detection of liver cancer helps to improve life expectancy.We also need to know the tumor status during treatment stages.Manual segmentation and detection is time consuming .Here we propose an automated computer aided diagnosis of liver tumors from CT images.Initially liver is segmented using MRF embedded level set method.It provides robustness to noise and fast segmentation. The shape ambiguities of the segmented liver is found out by shape analysis methods which uses training set for correction. From the corrected liver segmentation, hepatic tumors are detected by graph cut method and feature extraction is done to classify them using SVM classifier.

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Keywords: Liver tumor;MRF segmentation;Shape ambiguities correction;Tumor detection.

1. Introduction

Tumors are abnormal growth of tissue due to uncontrolled multiplication of cells and serving no physiological function,it can be either cancerous or non cancerous.

Liver carcinomas are one of the commonly occurring cancers in the real world.Tumors are originated in the liver either due to alcohol consumption or due to hepatitis B or C viruses. Liver metastases are hepatic cancers that have spread from another primary source in the body.

The liver is a prime candidate for metastases from cancers in the breast, colon, prostate, lung, pancreas, stomach, esophagus, adrenal glands, or skin (melanoma). A hepatic metastasis can be found at the time of the diagnosis of the

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primary cancer or appear later after the removal of the primary tumor. Although secondary liver cancer is generally untreatable,treatments may improve life expectancy.

In traditional clinical practice, 3-D organ analysis is performed via time consuming manual measurements. There are several advantages that automated methods have over manual or interactive techniques.Automated techniques are faster and donot need human presence.

Computed tomography (CT) is used to analyse internal organs for diagnosis and preoperative planning.It provides 3D view of abdominal organs and their shape and volume analysis help to detect disorders.Also it can be used to analyse the improvement in treatment at various stages.

The rest of the paper is organized as follows:Section 2 describes the related works to the paper.Section 3 describes the proposed method in detail and finally section 4 gives the conclusion.

Nomenclature

CT	Computed tomography
MRF	Markov Random Field
SFM	Sparse Field Method
SVM	Support Vector Machine

2. Related Works

Masuda, Yu, et al.[3]. uses EM algorithm for tumor detection.First the noise is removed by preprocessing.Preprocessing is done based on intensity values.Then EM algorithm is performed to cluster the liver tissues.Then false positives are removed by shape informations.This can decrease the false positives.

Militzer, Arne, et al. [4]detect and segment lesions on liver from contrast enhanced ct image. Input the venous enhanced ct image.Then segment the liver and we label each pixel on the liver as either a lesion or a healthy tissue based on intensity.The method gives 77% accuracy and contrast enhanced CT data is needed.

Jayanthi, M., and B. Kanmani,et al.[5] proposes an approach for segmenting liver and tumor using intensity distribution and region growing method.Preprocessing is done first.Then using histogram and erosion we remove unnecessary parts of abdomen.Region growing is applied to segment the liver and tumors.

Linguraru, Marius George, et al. [1] presents an automated computaion of liver burden from CT image.Initially liver is segmented .Any ambiguities in segmenation is addressed by shape parametrization and geodesic active contour corrects the dissimilarity if any.Then hepatic tumors are segmented and classified into cancerous or not.The proposed method gives good result but performance is less for noisy image.

Yang, Xi, et al. [2]presents a robust levelset method for image segmentation.Robustness to noise is achieved by embeding a MRF(Markov Random Field) to the level set energy function.The MRF function consider correlation among pixels sothat they fall into same category.For fast implementation of this we use SFM(Sparse field Method).This method can segment noisy image in 3s.

In the proposed method, the above segmention method is combined with [1],we can overcome the low performance issue in noisy images. Shape ambiguity correction is also done in order to refine the segmentation.

1. Proposed System

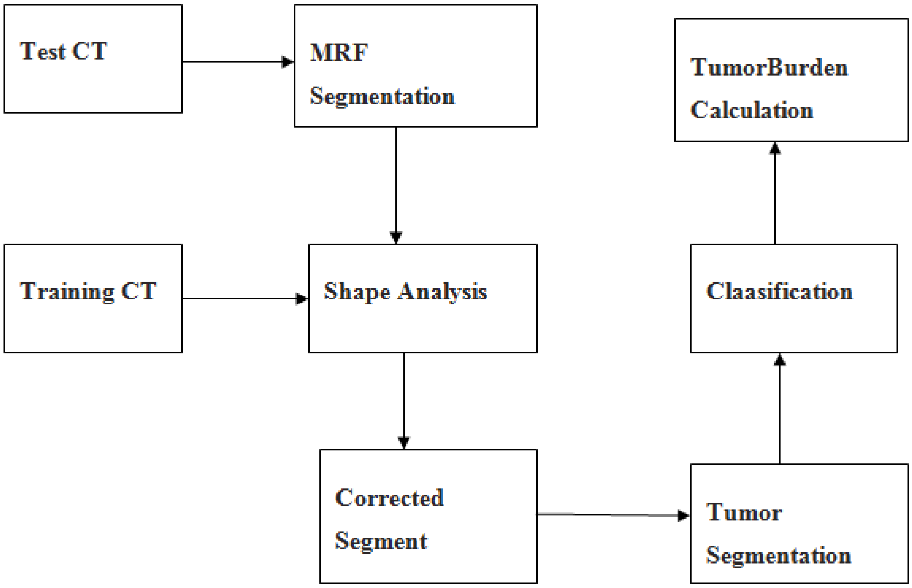

Fig.1.Block Diagram Of Proposed Method

3.1. MRF Segmentation

Segmentation is the process of assigning labels to each of the pixels in an image so that pixels with same label have some common properties.It helps to represent the image so that it is easy to analyse it. It serves as the assistance to many tasks such as object recognition and image understanding especially in medical image.

Level set methods implicitly model the planar closed curve C by the zero level set of the level set function f(x, y, t) ie

$$C(t) = \{(x, y)|f(x, y, t) = 0\} \quad (1)$$

Image segmentation using level set methods can be viewed as a procedure in which a contour is evolved to the object boundary by minimizing a certain energy function,associated with the level set equation.Level set methods are of two types : edge based and region based.In edge based,a stop function is designed using image gradient flow and put in the activecontour.(eg.Geodesic Active Contour)[10].Region based exploits region descriptors to guide the motion of active contour.(segmenting image into intensity homogeneous regions.)As level set try to minimize energy term,it may stuck in local minimum.To avoid this graph cut methods are used,as it operates by finding a globally optimal cut through the graph based on the input data.

All these methods are good in segmenting high quality images but gives poor result in noisy images.The main reason for this is each pixel are considered independent while calculating energy function.This makes it sensitive to noise.Also computation is performed on full image domain,but pixels far way from the contour is meaningless.It makes the implementation of level set time consuming which limits its use in large databases.

To make the level set robust to noise a MRF energy function[11] is embedded to traditional level set function.It consider relationship between neighbouring pixels. The proposed model builds an energy function framework as

$$E = E_{internal} + E_{external} + E_{MRF} \tag{2}$$

It consists of three terms corresponding to internal energy function, external energy function and MRF energy function, respectively. The internal energy function is denoted by characteristics of the evolving contour itself, such as its curvature, length and area. The external energy function concerns the evolution force determined by image information which has no association with the evolving contour. The MRF energy function finds the best segmentation label for each pixel by considering the neighbouring pixels using the Bayes theorem.

The computation of level set is carried out on full image domain so it takes a lot of time. The sparse field method (SFM)[12] reduce the computational complexity by only performing calculations near the zero level set. The sparse field method(SFM) uses lists of points that represent the zero level set as well as points adjacent to the zero level set to calculate the object boundary. By carefully moving points to and from the list an efficient representation of image is obtained.

Five doubly linked list is used for implemtation.Doubly linked list has property that elements can be added and removed at any time from any where in the list.Five list $L_{-2,}L_{-1,}L_{0,}L_{1,}L_2$ which holds x,y,z locations of points are used.Also a label map array which stores the status of each point is used.It indicates to which list each point belongs.

3.2.Shape Analysis & Correction

To find shape ambiguities,a number of parallel hyper planes were drawn on the object surfaces,such that we get a closed planer curve on the intersection of plane with the the object.A shape feature S is defined as the volume of interior of intersection of the plane with the object.This shape feature is used to detect shape dissimilarity.

Parallel hyper planes are drawn by uniform sampling. ie the planes are partitioned into equal samples and is projected to object surfaces to get liver shape parametrization. Each intersection of the planes with the liver is then analyzed and the average number of connected components is found. The minimum sum of average components across the corresponding axes/planes of the two compared objects (test and training image)is then computed. This defines the set of matched convexity planes.At each intersection we calculate the shape feature for both the image and their absolute difference gives the dissimilarity. The dissimilarity is then averaged as the mean value between dissimilarities with all training shapes. By using the average, we avoid similarity to a single shape in the reference database that may be itself unusual.We also set a threshold to allow intra patient dissimilarities.Then a fast level set method based on the gradient of image is applied to get the corrected liver segment.The threshold value is set as the stop function for the level set.

3.3.Tumor Segmentation & Classification

Liver tumors are segmented by graph cut method from liver surfaces. Our goal will be to segment an image by constructing a graph such that the minimal cut of this graph will cut all the edges connecting the pixels of different objects with each other.We differentiate objects with the histogram fitting.

Using minimum redundancy maximum relevance feature extraction method[9] 157 features including size,enhancement etc were calculated for each tumor.These features are then given as input to the SVM classifiers to classify the tumors as cancerous or not.

3.4.Tumor Burden Calculation

The total volume of tumors was computed for each patient and normalized by the total liver volume to compute tumor burden.

3. Conclusion

The proposed method for liver tumor detection and segmentation provides a robust tool for liver tumor diagnosis. MRF embedded level set method make it robust to noise and motion artifacts.Sparse Field Method helps in the fast segmentation. Shape ambiguity can be corrected by shape analysis and tumors can be accurately segmented and classified.It helps radiologists and surgeons to have easy and convenient access to organ measurements and 3-D visualization and they can use this as a second opinion for tumor detection.

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