Detection of Gastrointestinal Stromal Cancer Cells using Image Processing

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Abstract- *Image processing plays a major role in biomedical applications in order to detect many diseases which affects human. It detects the gastrointestinal stromal cancer which affects the digestive system at the stomach. Image processing made it possible to detect, locate, provide the pre-state analysis of cancer and its stages. It uses image segmentation techniques such as threshold segmentation, clustering, edge detection, morphological operations and region based segmentation. Image segmentation process the PET scanned image according to the partitioning of images into its constituent regions or objects. It also uses image enhancement technique to highlight certain features of interest in an image. It is a subjective process which means that the human perception decides the best method from the obtained results. The approach of enhancement process involves the spatial domain and frequency domain methods. It also involves the image mask processing by processing an image in a array basis. The image can be functioned by considering several geometric properties based on the shape, structure and dimension of the gastrointestinal stromal cancer cells. The results of this detection provides the accuracy in measurements and pre-state information of the cancerous cells.*

Keywords- Gastro intestinal sromal cancer, Image segmentation, Noise removal, Bilateral Filtering, Hidden Markov model, Robert forest(RF), PET scan, Histogram estimation, Dice score.

I. INTRODUCTION

Gastrointestinal stromal cancers are uncommon cancers which start in very early forms of Interstitial Cells of Cajal (ICCs). ICCs are the part ofthe nervous system which regulates the process of the digestion. It signals the muscles in order to contract to move the food and the liquid throughthe gastrointestinal tract in the digestive system. Not all the gastrointestinal tumours are cancerous. Some of them are benign which are non-cancerous and don't grow into other areas or spread to other parts of the body.

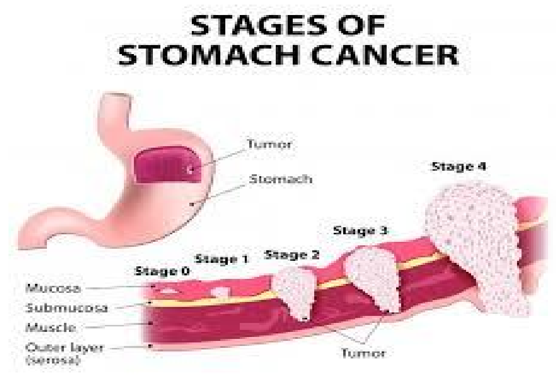


Fig 1 Stages of stomach cancer

There are various kinds of tumours in the gastrointestinal tract. Each cancer has a different prognosis and it is the challenging risk to detect the type which is cancerous, non-cancerous, and other types of cancers. About 70% of this cancer occurs in the stomach, 20% in the small intestine and less than 10% in the esophagus. When the cancer is not determined earlier it disseminate to the liver, omentum and peritoneal cavity. It rarely occurs in the abdominal organs.

II. THEORETICAL BACKGROUND

In the proposed system, it deals with the image segmentation process in which the PET scanned images are functioned by the partitioning of regions or an objects of an image. It also involves several techniques such as Image enhancement, Noise removal, Histogram likelihood estimation and Generative and discriminative probabilistic approaches. It calculates accuracy score, sensitivity and specificity values of the proposed method. To obtain high quality PET images from noisy projection data, many approaches have been explored. They can be coarsely divided into three categories: pre-processing methods, iterative reconstruction approaches and post-processing algorithms.

Pre-processing methods restore the projection data before standard filtered-back projection (FBP) reconstruction, mainly including nonlinear noise filters and statistic-based iterative de-noising methods. Iterative reconstruction approaches treat the LDCT imaging as an ill-posed inverse problem, and solve the problem by minimizing an objective function, which often includes a data fidelity term and a regularization term.

Post-processing approaches are directly applied on LDCT images reconstructed by FBP methods to suppress noise and streak artifacts, ensuring that neither important tissue structures are lost nor false structures introduced. In a large-scale nonlocal means (LNLM) technique was proposed to suppress noise in abdomen LDCT images. This LNLM method was further combined with a directional 1D nonlinear diffusion to suppress streak artifacts in thoracic CT images .In a sparse representation theory, a fast dictionary learning (DL) method was proposed to remove the artifacts and noise in abdomen cancer LDCT images. However, when strong artifacts appear in the LDCT image, they are hard to be suppressed via the DL method. This is because streak artifacts can lead to the same large sparse coefficients as tissue structures. To solve this problem, an artifact suppressed dictionary learning (ASDL) algorithm was proposed to improve LDCT images. The streak artifacts in LDCT images are suppressed by a discriminative sparse coding in high frequency bands. Three novel discriminative dictionaries are respectively designed to characterize artifact and normal tissue feature components in different orientations, the general DL processing is applied to further suppress the noise and residual artifacts.

III. MODULE DESCRIPTION

1. PET SCAN INPUT IMAGE

It is an imaging test uses special dye has radioactive tracers which is inserted into the human body in order to locate the disease or an abnormal areas. This dye can be inserted through the air inflow by which the tissues can absorb the tracer. It shows the problems at the cellular level and it detects how the cancer metabolizes, spread or metasized to the new areas. It is less exposure to harmful radiation and it gives the accurate clear imaging analysis than the CT scan image. It does not use the x-ray beams inside the body.

BLOCK OF THE PROPOSED SYSTEM

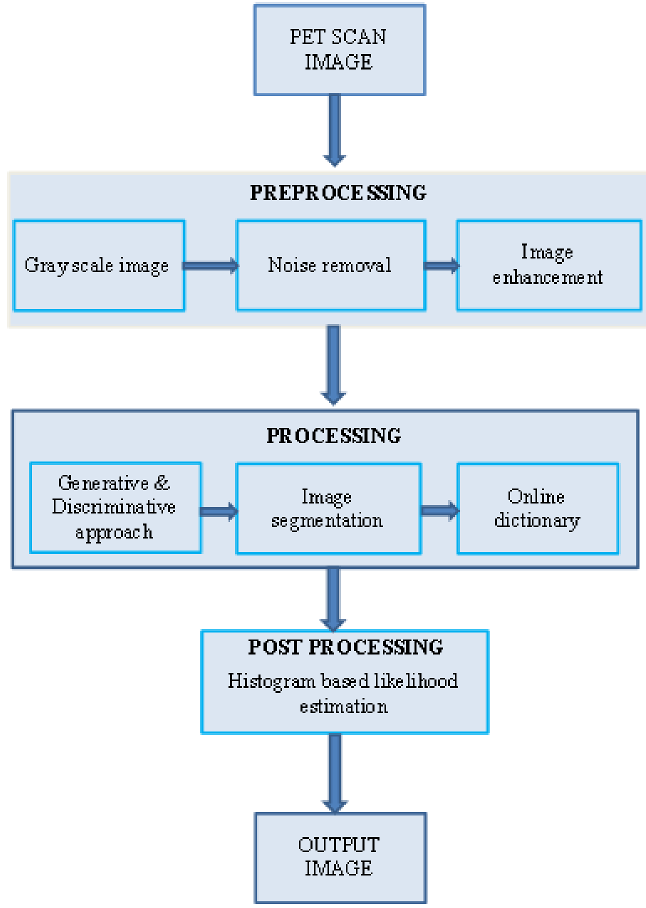


Fig 2 Block diagram of proposed system

2. PREPROCESSING

In the pre-processing step, it decompose an LDCT image into the LF and HF parts by applying BF. This filter can smooth an image while preserving edges. It note that the filter can be replaced by the K-SVD-based filtering technique .It shows an example of producing *HF* using BF and the K-SVD-based filtering techniques respectively.

A. BILATERALFILTER

Bilateral filter was originally proposed by Tomasi and Manduchi as a non-iterative and locally adaptive method for removing noise from images while preserving edge information.

$$I(i,j) = \frac{\sum_{k,j\epsilon N_{ij}} I(k,l)\omega(i,j,k,l)}{\sum_{k,j\epsilon N_{ij}} \omega(i,j,k,l)}$$

B. MCA - BASED ARTIFACT REMOVAL METHOD

The first step aims at decomposing an LDCT image into the LF part and the HF part,

$$I = I_{LF} + I_{HF}$$

Once it is obtained, it learn a dictionary from by applying an efficient online DL method , which minimizes a cost function with the regularization term,

$$\min_{D_{HF,\theta^K}} \frac{1}{l}\sum_{K=1}^{l}\left(\frac{1}{2}\|I_{HF}{}^{K} - D_{HF}\theta^{K}\|^2+\mu\|\theta^{K}\|\right)$$

3. IMAGE SEGMENTATION

Many state-of-the-art algorithms for cancer segmentation are based on techniques originally developed for other structures or pathologies, most notably for automated white matter lesion segmentation that has reached considerable accuracy .While many technologies have been tested for their applicability to gastric cancer cell detection and segmentation—e.g., algorithms from image retrieval as an early example. A possible direction that avoids the calibration issues of discriminative approaches, as well as the limitations of generative models, is the development of joint generative-discriminative methods. These techniques use a generative method in a pre-processing step to generate stable input for a subsequent discriminative model that can be trained to predict more complex class labels.

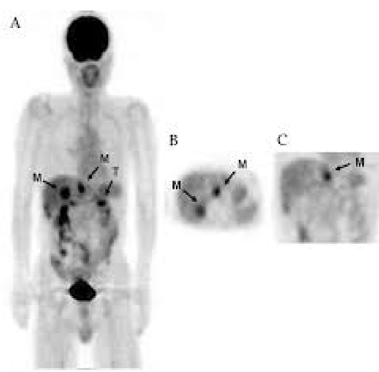


Fig 3 MRF graph cuts

The hierarchical majority vote algorithm is used for this method of image segmentation which follows,

label ← "nrm"
if(n_{edm}+n_{nen}+n_{nec}+n_{enh})≥ n_{all}/2 **then**
label ← "edm"
if (n_{nen}+n_{nec}+n_{enh})≥ n_{all}/2 **then**
label ← "nen"
if (n_{nec}+n_{enh})≥ n_{all}/2 **then**
label ← "nec"
if (n_{enh})≥ n_{all}/2 **then**
label ← "enh"
end if
end if
end if
end if

4. POST PROCESSING

The context-inducing component is the use of context-sensitive features for the forest which capture intensity characteristics around the point of interest. Due to the regularizing effect of the context-sensitive forest, which could not find it necessary to use an explicit energy-based regularization.It learn individual classifiers for the four sub-tasks (real/ high, real/low, sim/high, sim/low). Since it does not perform a cross-validation to modify any parameters for the 4-class setting, the error reported in the system for 4-class training is based on a classifier trained on all images, which explains the high score.

The histogram based likelihood estimation algorithm further increases the image segmentation, accuracy and the computation of deformed histogram of an image.

Input :img_x
Labelledimage :img_i
1. Compute i_i, $i_x$with quantization
2. Compute H_i, H_x, $H_{t,i}$, $t \in L$
3. With H_i, H_x, compute T_x^ix
4. With T_t^ixand $H_{t,i}$, compute deformed histogram
5. $Pr_i(\mathsf{I}(\mathsf{p})|f_p) = H_{fp,i}(I_x(\mathrm{p}))$

IV. CALCULATION

By evaluating multiple binary segmentation tasks, it also avoid the problem of specifying misclassification costs for trading false assignments in between, for example, edema and necrotic core structures or enhancing core and normal tissue, which cannot easily be solved in a global manner.

1. PERFORMANCE SCORES

For each of the three tumor regions ie obtained a binary map with algorithmic predictions P ∈ {0,1} and the experts' consensus truth T ∈ {0,1}, and it has been calculated the well-known Dice score,

$$\textbf{Dice (P, T)} = \frac{|P_1^{T_1}|}{(|P_1|+|T_1|)/2}$$

where^ is the logical AND operator,|.| is the size of the set (i.e., the number of voxels belonging to it), and and represent the set of voxels where and , respectively . The Dice score normalizes the number of true positives to the average size of the two segmented areas. It is identical to the F score (the harmonic mean of the precision recall curve) and can be transformed monotonously to the Jaccard score. It also calculated the so-called sensitivity (true positive rate)and specificity (true negative rate).

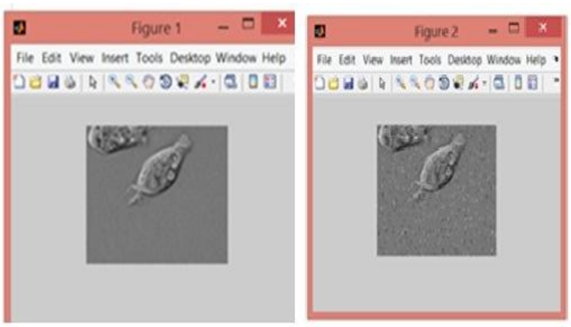
$$\textbf{Sens (P, T)} = \frac{|P_1^{T_1}|}{|T_1|)}$$

$$\textbf{Spec (P, T)} = \frac{|P_0^{T_0}|}{|T_0|)}$$

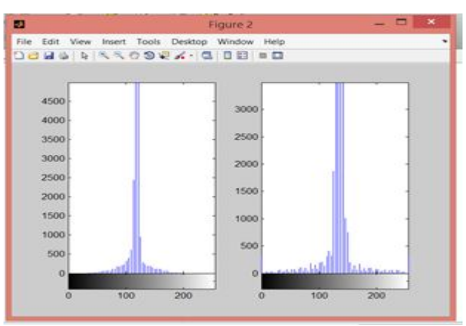
V. SIMULATION RESULTS

Visualization functions and apps explore images and videos, examine a region of pixels, adjust color and contrast, create contours or histograms, and manipulate regions of interest. The toolbox supports workflows for processing,displaying, and navigating large images.

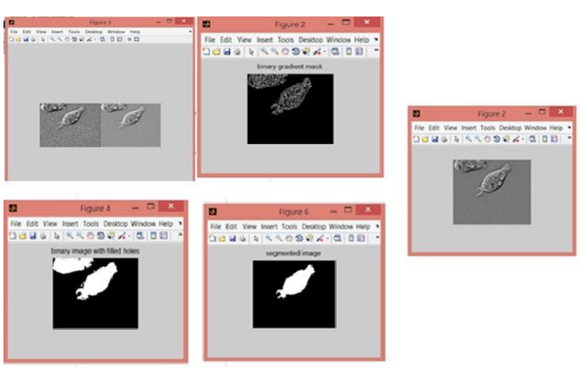
1. NOISE REMOVAL



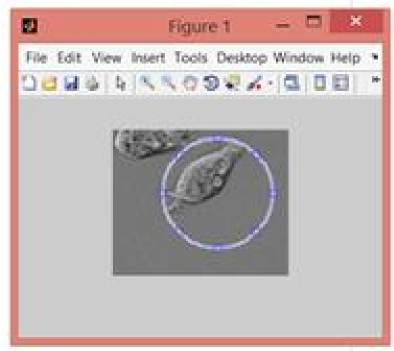
2.IMAGE INTENSITY



3. IMAGE SEGMENTATION



4.REGION OF INTEREST



VI. CONCLUSION

Image processing techniques helps to detect the stomach cancer accurately with a lot of new way of techniques. The image segmentation deals with the accurate location of the cancer cell using the generative and discriminative approaches. The online dictionary learning method obtains the quick search of databases of the related images. Thus the image processing has been used to save the human lives from the cancer .

VII. FUTURE ENHANCEMENT

The image classification of Robert Forest (RF) analysis can be developed at the prediction of tissue labels. The preprocessing techniques are improved at the Slice co-registration, Bias field and intensity and bone stripping. The Map reduce model for the Hidden Markov Model(HMM) has been obtained at the multilevel analysis of the segmented images.

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