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Liver and Tumor Segmentation using Graph-Cut and Geodesic Graph-cut method

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Abstract Automatic Initialization technique depends on Statistical model appropriation of liver normal force and Standard deviation. Tumor division required likewise an indistinguishable programmed instatement from that of the liver. This progression was connected just to liver volume, acquired after programmed depiction of liver surface: this last mentioned, connected to unique dataset volume, was utilized as a veil with a specific end goal to forestall handling over-burdens and stay away from blunders identified with the nearness of encompassing tissues introducing comparative dim scale dispersions. Furthermore, for this reason, the voxels having a place with the force go area were likewise expelled from the sectioned liver volume. This decision permitted the right distinguishing proof of liver regard to different organs, improving the computation assets and expanding the tumor division precision.

Keywords: Graph Cut method, Geodesic Graph Cut method, Active Contours.

I. Introduction

Liver cancer is a standout amongst the most unpleasant tumor maladies and causes a lot of death consistently. The liver disease is a standout amongst the most well-known interior malignancies around the world. The hepatocellular carcinoma is regular in Asia and metastasis is normal in the West. Among the dominating growth sorts, liver tumor positions at fourth place and is a rising reason for death on the planet. Every year, 1million new patients are determined to have essential liver growth, of which roughly 60% kicked the bucket in 2002. Liver Cancer has created expanded death rate in the course of the most recent 5 years. As indicated by 2008 year insights, more than 3390 individuals from UK alone were determined to have liver disease. By 2010, the determination forget about expanded upto 4,241 and of which 3789 passed on of liver tumor. Hence, liver intercession is a standout amongst the most requesting fields in surgery. In any case, the treatment of essential and dangerous liver tumors relies on upon the spatial degree of the malady inside the liver, and in addition outside the liver, and on the general wellbeing states of the patient. Individual preoperative surgical making arrangements for resections of tumors in the liver requires division of the liver tissue. Solid picture division is basic for the right expectation of the blood flow districts. Self-loader strategies may diminish the client connection time for division.

However in the clinical standard, programmed strategies are alluring. 3D measurable shape models are promising for vigorous and programmed division of medicinal pictures. At the point when no tumor is identifiable outside the liver, nearby treatment is more proper since it causes less reactions. If there should be an occurrence of a harmful tumor, the specialist needs to pick among various neighborhood medications: radiotherapy, liver resection, cryoablation, and radio-recurrence removal .Planning a liver intercession dependably displays a test for the specialist, even with the quickly developing comprehension of liver life structures and pathology of patients and the accessibility of mechanical guides for surgical strategy. To be sure, therapeutic choices are once in a while taken without the utilization of imaging innovation including figured tomography (CT), attractive reverberation (MR) imaging, and ultrasound (US). Advance accomplished in these procedures licenses recognizing littler tumors than before, hence permitting prior analysis and treatment. Hence, the accomplishment of present day and future liver mediations depends likewise on programming fit for helping professionals worried, for example, PC helped conclusion, surgical arranging, and reenactment. Any sort of liver nearby treatment (surgical or not) requires a similar data: a fine liver surface division, exact size and confinement of tumors, precise liver vessel geography, and relative spatial relations among these tissues. To face this test, liver division has been broadly canvassed in the writing in late decades and keeps on being a developing field with open research issues. Picture division is an exemplary issue in PC vision. It is a procedure that parcels the picture pixels into significant gatherings with the goal that we can accomplish a minimal portrayal of the picture. Division is typically performed in view of many variables, for example, force, shading, or surface similitudes, pixel progression, and larger amount learning about the items display.

Picture division has numerous applications in the biomedical field. In medicinal picture investigation, picture division is a central and testing issue. Regardless of a very long while of research and many key advances, a few difficulties still stay around there. An Efficient, strong, and programmed division of life structures on radiological pictures is one such test. Medicinal imaging has turned into an essential part in social insurance these days. X-beams, ultrasound, PC tomography (CT) and attractive reverberation (MR) pictures have been standard demonstrative strategies that are performed in healing facilities and centers.

CIRHOSSIS, lymphoma, pancreatitis, Hodgkin's malady, and renal cell carcinoma, are only a couple of the numerous infections that can be analyzed utilizing CT sweeps of the guts. The advancement of PC supported finding frameworks would permit anatomical information combined with picture preparing strategies to enhance human services. Information of life systems is just of utility if that learning is connected to the expulsion of ailment and to the protection of wellbeing. PC based frameworks for the investigation of CT pictures have many favorable circumstances over human mediators, for example, speed, huge learning base for analytic data, and non-affectability to weariness.

Organ division is regularly the initial phase in PC helped conclusion. Division of stomach organs, for example, the liver, kidneys, and spleen, from CT examine symbolism has been pulling in a decent measure of research as of late. Division of stomach organs presents many difficulties. Numerous ancient rarities can emerge in CT examines, among these are bar solidifying curios, which are perceptible as central zones of low weakening neighboring bones; halfway volume antiques, coming about because of spatial averaging of dissimilar tissues in closeness and bringing about obscured edges; and streak relics, the aftereffect of peristalsis, respiratory, heart, and patient movement. Likewise, unique organs and tissues have fundamentally the same as dim levels, which entrust thresholding to restricted utility.

Indisputably the dim levels watched additionally fluctuate generally with the example of operation. Advance challenges emerge because of absence of organ tissue homogeneity inside and among various picture cuts, both fit as a fiddle and surface. Extra challenges are related with the way that there is no exact metric for execution assessment. Thusly restorative picture examination has turned into a sharp research point in picture handling and PC vision. Picture division alludes to the way toward parceling a computerized picture into numerous portions (set of pixels). The objective of division is to rearrange or potentially change the portrayal of a picture into something that is more significant and simpler to break down. Picture division is commonly used to find articles and limits (lines, bends, and so forth.) in pictures. All the more absolutely, picture division is the way toward relegating a mark to each pixel in a picture to such an extent that pixels with a similar name share certain visual attributes.

II. MATERIALS AND METHODS

Abdel-Massieh.N.H. et al. [1] evaluated the completely programmed and productive procedure for liver division from stomach CT pictures which depends on Fast Marching to portion liver districts from Multi-cut Spiral Computed Tomographic Images. The paper proposed a completely programmed technique to portion liver areas from MSCT. In any case, connections between's neighbor cut pictures were gotten to get beginning fronts. At that point an altered quick walking was connected to engender the fronts until stop standard was fulfilled. The ranges included by the proliferated fronts were the liver districts. Finish liver districts of one case could be brought from each cut utilizing comparable approach one by one. This paper assessed nearby and worldwide data which gave exact liver limit and there was great Correlation between neighbor cut pictures. Be that as it may it doesn't function admirably when liver tissues have different forces with nearby organs volumetric estimation and 3D representation of liver.

Ben-Dan.I. et al. [2] investigated the Liver Tumor division strategy in CT pictures utilizing probabilistic strategies which depend on Chan-Vese technique (Energy based Segmentation) utilizing power probability proportion test. Initial an underlying histogram and measurable dissemination capacities are made, and from them another picture is made where, in each voxel, a weighted capacity is appended as per the likelihood of the voxel dark level. Next, the dynamic shape technique on the new picture is utilized, where the dynamic form development depends on the minimization of fluctuations between the liver tumor and its nearest neighborhood. Here blend of techniques for earlier investigation and vitality based division is utilized. Vitality construct division is situated in light of Active shapes strategy without edges and Active form and division utilizing geometric Probability Density Energy work. Productive numerical techniques were created for veins division and for liver division. The Segmentation method utilized has delivered better and less commotion delicate outcomes. However vessels division is not appropriately approved and liver parceling is not done legitimately which are the real impediments.

Boykov.Y. et al. [3] assessed a vital answer for surface development PDEs by means of geo-cuts technique which models inclination streams of shapes and surfaces. While standard variational techniques (e.g. level sets) register neighborhood interface movement in a differential mold by assessing nearby form speed by means of vitality subsidiaries, surface development PDEs was unraveled by expressly evaluating essential movement of the entire surface. An improvement issue was defined straightforwardly in light of an essential portrayal of inclination stream as a microscopic move of the (entire) surface giving the biggest vitality diminish among all moves of equivalent size. This issue can be effectively comprehended utilizing late advances in calculations for worldwide hyper surface enhancement. Specifically, the geo-cuts strategy was utilized that utilizations thoughts from essential geometry to speak to persistent surfaces as cuts on discrete diagrams. The subsequent interface advancement calculation is approved on about 2D and 3D cases like normal shows of level-set techniques. This technique can figure slope streams of hyper surfaces regarding a genuinely broad class of consistent practical and it is adaptable as for separation measurements on the space of forms/surfaces. The calculation produces an auspicious grouping of slices relating to angle stream of a given form. This technique is not another usage of level set strategies but instead an option numerical strategy for developing interfaces. Our technique does not utilize any level set capacity to speak to forms/surfaces. Rather, it utilizes an understood form/surface portrayal by means of geo-cuts. As the level set technique, this approach handles topological changes of the developing interface. A fundamental approach was utilized to fathom a specific class of angle stream PDEs. To this end, effective combinatorial advancement techniques were followed up on a discrete space. Different streamlining issues characterized on surfaces in constant spaces can be proficiently explained by discrete combinatorial advancement strategies. As opposed to these works, the present paper is not centered around deciding the worldwide optima of separate cost capacities, yet rather on really displaying the neighborhood slope plummet development of the comparing variational approaches. This strategy was adaptable w.r.t separate measurements on the space of shapes/surfaces. Nonetheless, this technique is essentially hypothetical and Distance guide can be resolved just with accuracy 0.5 with uncontrolled time steps.

Grady.L. et al. [4] checked on the Random Walker approach for general picture division which depends on little arrangement of pre-marked pixels. Given few pixels with client characterized (or pre-characterized) marks, one can systematically and rapidly decide the likelihood that an arbitrary walker beginning at each unlabeled pixel will initially achieve one of the pre-named pixels. By appointing every pixel to the name for which the best likelihood is figured, top notch picture division might be gotten. Hypothetical properties of this calculation are created alongside the comparing associations with discrete potential hypothesis and electrical circuits. This calculation is figured in discrete space (i.e., on a diagram) utilizing combinatorial analogs of standard administrators and standards from constant potential hypothesis, enabling it to be connected in self-assertive measurement on subjective charts. The irregular walker calculation requires the arrangement of a scanty, symmetric positive-distinct arrangement of direct conditions which might be unraveled rapidly through an assortment of techniques. The calculation may perform quick altering by utilizing the past arrangement as the instatement of an iterative network solver. A subjective division may likewise be accomplished sufficiently through client communication. Each seed determines an area with a client characterized name. A last division might be gotten from these K-tuples by choosing for every pixel the most plausible seed goal for an arbitrary walker. This Random Walker approach for general picture division was for the most part hearty to frail protest limits and it assesses client's pre-naming decisions. Be that as it may, it expends immensely expansive calculation time and it was utilized just as an underlying answer for an iterative framework solver.

Lim.S.J. et al. [5] looked into the Automatic liver division for volume estimation in CT pictures which depends on unsupervised Automatic Liver Segmentation Algorithm (Region-based + Contour-based Approaches). An unsupervised liver division calculation is given three stages. In the preprocessing, the information CT picture is streamlined by evaluating the liver position utilizing an earlier learning about the area of the liver and by performing multilevel edge on the assessed liver position. The proposed

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conspire uses the multiscale morphological channel recursively with district naming and bunching to identify the look extend for deformable forming. The vast majority of the liver shapes are situated inside the inquiry extend. Keeping in mind the end goal to play out a precise division, the slope name guide is created, which speaks to the angle greatness in the hunt run. The proposed calculation performed deformable forming on the inclination mark outline utilizing standard examples of the liver limit. Test results are practically identical to those of manual following by radiological specialists and appeared to be productive. This programmed liver division calculation in stomach CT pictures is a mix of district based and shape based methodologies. The calculation abuses multiscale morphological sifting and the deformable form technique utilizing naming based pursuit calculation to address these issues. With a specific end goal to expand the strength of the strategy, ELP is utilized, which is made out of control focuses and fitted into the patient guide. ELP empowers us to discover powerful patient form and is utilized to perform appropriate liver division. For the most part, the liver is approximated to muscle and gastrointestinal tract. Since contiguous organs have comparative force values as the liver, an immediate liver-extraction approach may remove undesirable limits coming about because of its neighboring organs as blame positive/negative blunders. Keeping in mind the end goal to adapt to the issue, another division plan is exhibited, comprising of three phases: picture disentanglement as preprocessing, inquiry go recognition utilizing multiscale morphological sifting, and form based division utilizing the marking based hunt calculation. The Gradient-Label Map utilized as a part of this paper gave exact division and the Estimated Liver Position performed legitimate liver division. However the strategy does not assess Dice Similarity Coefficient and it delivered a manual blunder of around 3.2%.

III. METHODOLOGY

The microstructure assessment of any material structures the fundamental stride before assessing its properties. It is a situation in which we can see the stage piece of the constituent components. It likewise shows the structure of the grain which is essential for assessment of the properties. As a matter of first importance Application of preprocessing channel to unique volumetric picture is continued for commotion expulsion from homogenous zones. Here each cut of separated volume is isolated into 64 squared sub districts. For every stomach sub district, computation of mean picture power and standard deviation is done to distinguish most homogeneous areas regarding pixel force. Next, Selection of middle with standard deviation is performed. At long last Images are apportioned and liver locales are recognized.

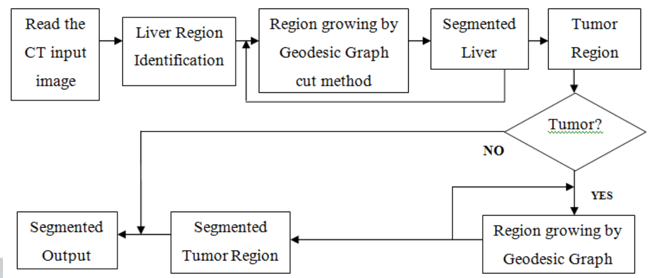

Fig.1. Proposed Method

Mean shift is a general nonparametric procedure for the investigation of complex multimodal highlight space and to depict formed bunches in it. The essential computational module of the method is an old example acknowledgment system, the mean move. The connection of mean move to the Nadaraya-Watson estimator from bit relapse and the powerful M-estimators of area is likewise settled. The main client set parameter is the determination of the investigation and either dark level or shading pictures are acknowledged as info.

Mean Shift is a capable and flexible non parametric iterative calculation that can be utilized for parcel of purposes like discovering modes, grouping and so on. Mean Shift has been reached out to be appropriate in different fields like Computer Vision. Mean move considers include space as an experimental likelihood thickness work. On the off chance that the information is an arrangement of focuses then Mean move considers them as examined from the hidden likelihood thickness work. In the event that thick districts (or groups) are available in the element space, then they relate to the mode (or nearby maxima) of the likelihood thickness work. We can likewise distinguish bunches related with the given mode utilizing Mean Shift.

For every information point, Mean move partners it with the close-by pinnacle of the datasets likelihood thickness work. For every information point, mean move characterizes a window around it and registers the mean of the information point. At that point it moves the focal point of the window to the mean and rehashes the calculation till it joins. After every cycle, the window movements to a denser locale of the dataset.

At the abnormal state, Mean Shift strategy can be indicated as takes after:

1. Settle a window around every information point.
2. Process the mean of information inside the window.
3. Move the window to the mean and rehash till merging.

Bit thickness estimation in mean move is a non parametric approach to evaluate the thickness capacity of an irregular variable. This is generally called as the Parzen window method. Mean move treats the focuses the element space as a likelihood thickness work. Thick districts in highlight space relate to neighborhood maxima or modes. So for every information point, inclination climb is performed on the neighborhood assessed thickness until union. The stationary focuses acquired by means of angle climb speak to the methods of the thickness work. All focuses related with the same stationary guide have a place toward a similar bunch.

Despite the fact that mean move is a non parametric calculation, it requires the data transmission parameter h to be tuned. kNN calculation can be utilized to discover the transfer speed. The decision of data transmission impacts the estimation of merging rate and the quantity of groups. Decision of transmission capacity parameter h is basic. A vast h may bring about off base bunching and may combine unmistakable groups. A little h may bring about an excessive number of groups.

When utilizing kNN to deciding h, the decision of k impacts the estimation of h. For good outcomes, k esteem needs to increment when the measurement of the information increments. Mean move won't not function admirably in higher measurements. In higher measurements, the quantity of neighborhood maxima is truly high and it may unite to nearby optima soon. panechnikov portion has a reasonable cutoff and is ideal in predisposition fluctuation tradeoff.

Mean shift is a flexible calculation that has found a considerable measure of down to earth applications – particularly in the PC vision field. In the PC vision, the measurements are generally low (e.g. the shading profile of the picture). Consequently mean move is utilized to perform part of normal undertakings in vision.

The most imperative application is utilizing Mean Shift for grouping. The way that Mean Shift does not make suspicions about the quantity of groups or the state of the bunch makes it perfect for taking care of groups of subjective shape and number. Albeit, Mean Shift is principally a mode discovering calculation, we can discover bunches utilizing it. The stationary focuses got through inclination rising speak to the methods of the thickness work. All focuses related with the same stationary guide have a place toward a similar bunch. A substitute path is to utilize the idea of Basin of Attraction. Casually, the arrangement of focuses that merge to a similar mode frames the bowl of fascination for that mode. Every one of the focuses in a similar bowl of fascination are related with a similar group. The quantity of groups is gotten by the quantity of modes. Mean Shift is utilized as a part of different assignments in Computer Vision like division, following, brokenness safeguarding smoothing and so on.

K-Means is one of most well known grouping calculations which can be contrasted and mean move strategy. It is straightforward, quick and proficient. Mean Shift can be contrasted and K-Means on number of parameters. A standout amongst the most essential contrasts is that K-implies makes two expansive suspicions – the quantity of bunches is as of now known and the groups are molded roundly (or circularly). Mean move, being a non parametric calculation, does not accept anything about number of groups. The quantity of modes gives the quantity of groups. Additionally, since it depends on thickness estimation, it can deal with self-assertively formed bunches.

K-means is extremely touchy to instatements. A wrong introduction can defer meeting or now and again even outcome in wrong groups. Mean move is genuinely strong to instatements. Normally, mean move is keep running for each point or in some cases focuses are chosen consistently from the component space. Likewise, K-means is delicate to exceptions yet Mean Shift is not extremely touchy. K-means is quick and has a period multifaceted nature. Executing the versatile limit procedure on this naturally extricated understanding particular information, the pictures were divided and afterward liver areas are recognized.

The Tumor Segmentation step was connected just to liver volume, acquired after programmed outline of liver surface. Moreover, for this reason, the voxels having a place with the power go area were additionally expelled from the sectioned liver volume. This decision permitted the right distinguishing proof of liver regard to different organs, enhancing the figuring assets and expanding the tumor division precision. Geodesic segmentation can be improved by inclusion of explicit edge information to encourage placement of selection boundaries on edges in the image and allow user more freedom in placing strokes. The region term alone can often carry the segmentation in such cases, but global color models without spatial locality information can often select disjoint regions. The use of geodesic distance can avoid selection of disjoint regions. This section presents how geodesic distances and edge information can be combined in a graph cut optimization framework, and then presents a way to use the predicted classification accuracy from the inferred color models to automatically tune the tradeoff between the strengths and weaknesses of the two.

The unary region term can be computed as follows:

$$R_1(x_i) = s_1(x_i) + M_1(x_i) + G_1(x_i) \quad (3.1)$$

where M $_l(x_i)$ is based on global color model as it is used for graph-cut segmentation, $G_l(x_i)$ is based on geodesic distance, and

$$s_1(x_i) = \{\infty, \text{if } x_i \in \Omega_1 \mid 0, \text{otherwise}\} \quad (3.2)$$

indicates the presence of a user stroke where Ī is the label opposite l (i.e. if l = F, then Ī = B). Fast Gauss Transform is used to compute foreground/background color models. P_l (c) is used for both global similarity and geodesic distances. M $_l$ (xi) is computed by

$$M_1(x_i) = P_i(C(x_i)) \quad (3.3)$$

G $_l$ (xi) is computed by normalizing the relative foreground/background geodesic distances

$$G_1(x_i) = \frac{D_1(x_i)}{D_F(x_i) + D_B(x_i)} \quad (3.4)$$

For boundary term we use:

$$B(x_i, x_j) = \frac{1}{1 + \| C(x_i) - C(x_j) \|^2} \quad (3.5)$$

where C(x) € [0,255].

To allow for global weighting of relative importance of the region and boundary components,

$$E(L) = \lambda_R \sum (R_{Li}(x_i)) + \lambda_B \sum (B(x_i, x_j)) |L_i - L_j| \quad (3.6)$$

The boundary weight serves the role of the traditional fixed region/boundary weighting in graph cut methods, and adjusted to individual images by considering only the size of the image (due to the disproportionate scaling of an objects area (unary term) and perimeter (boundary term)). The region weight λ_R is the relative weighting of the geodesic distance and other region components. Posterior probability of a pixel with color c belonging to foreground (F) or background (B) respectively is considered, assuming equal priority. This functions as a simple Bayesian classifier in which error can be estimated by

$$\varepsilon = \frac{1}{2}\left(\frac{\sum_{x\in F} P_B\, C(x)}{\Omega_F} + \frac{\sum_{x\in B} P_F\, C(x)}{\Omega_B}\right) \quad (3.7)$$

When there is no error (ε = 0), Color-based terms (M and G) are given full weight, and when the color models become indistinct (ε ≥0.5), they are given no weight:

$$\lambda_R = \begin{cases} 1 - 2\varepsilon, \text{if } \epsilon < 0.5 \\ 0, \text{otherwise} \end{cases} \quad (3.8)$$

The geodesic and boundary terms are further weighted based on the local confidence u(x) of the geodesic components:

$$u(x_i) = \left(\frac{|D_F(x_i) - D_B(x_i)|}{|D_F(x_i) + D_B(x_i)|}\right)^{\gamma} \quad (3.9)$$

where empirically γ= 2 to 2.5 works well.

To weight the geodesic component by u(xi), the region terms are redefined as follows:

$$R_1(x_i) = s_1(x_i) + M_1(x_i) + G_1(x_i) + u(x_i) G_1(x_i) \quad (3.10)$$

This maintains the weight of geodesic distance term.

Weighting of boundary costs are spatially adapted based on u(x) as follows:

$$B(x_i, x_j) = \frac{1 + \left(\frac{(u(x_i) + u(x_j))}{2}\right)}{1 + \| C(x_i) - C(x_j) \|^2} \quad (3.11)$$

When this geodesic confidence is low, this suggests that geodesic segmentation alone would consider this to be near a boundary, and the effect of the geodesic component is reduced, shifting control to the more accurate edge-finding term. The net effect of this spatially adaptive weighting is to both increase the relative weighting of the unary geodesic distance term and increase the cost of a boundary cut in what are clearly interior/exterior regions.

The Graph-Cut Technique solutions allow avoiding local minima, providing numerical robustness and do not use any shape-prior characteristics that would constrain too strongly recoverable shapes. The Graph-Cut Algorithm produces also better segmentation results than other fully automatic methods found in literature in both terms of accuracy and time processing.

To discriminate liver from background, we set a range threshold equal to 2σ. The initialization rules are as follows:

1) v (voxel) Є liver, if I(v) (image intensity of voxel) Є L2 (liver domain)
and v Є BIG.
2) v Є Background if I(v) Є B2 (Background domain) or if I(v) Є L2 and v
does not belong to BIG (biggest 18 connected component after thresholding).
3) v Є undetermined otherwise.

Here, Energy function relies on Region term and Boundary term. I (v) stands for the image intensity of voxel, and BIG for the biggest 18-connected component after similar thresholding. 3-D graph-cut method, conversely to active contour technique, is not iterative and is based on global minimization of defined energy function classes on a discrete graph. Energy function and penalties definitions were adapted to the specific liver segmentation purpose.

Then, energy function relies on two main terms: a) a region term (penalties depending on neighborhood context and on voxel labeling) and b) a boundary term (penalties based on adjacent voxels dissimilarity). For region term weights R_p, a patient-specific Gaussian model was used for the liver, thus providing a more faithful result than a-posteriori probability of object-labeled voxels. Then, for background, the a-posteriori probability was adapted taken into account all voxels but the ones initialized as liver in order to provide a non-null R_p also to undetermined voxels during initialization.

$$R_p(obj) = \frac{\exp\frac{-(I_P-\mu_{liver})^2}{2\,\sigma_{liver}^2}}{\sigma_{liver}\sqrt{2\pi}} \tag{3.12}$$

$$R_p(bkg) = -\ln\Pr(I_{P(obj)}) \tag{3.13}$$

a-posteriori probability for R_p (bkg) was evaluated on the histogram of the mean-shift filtered image for the voxels that were not initialized as liver. For boundary term, "directed" edge weights $w_{p,q}$ seem the best solution to encourage cuts from brighter object to darker background like liver in CT scans, and were defined as follows:

$$w_{p,q} = \begin{cases} 1, \text{if } Ip \leq Iq \\ \exp\left(\frac{-(Ip-Iq)^2}{2\sigma^2}\right), \text{if } Ip > Iq \end{cases} \tag{3.14}$$

Here σ, enabled to adjust the range of intensities taken into account to find the edges. Indeed small σ^2 encouraged edges between voxels with about the same intensities, while for big σ^2, intensity range was wider enabling contours to evolve with less constraints.

The cost function E can be defined as follows:

$$E = \sum w_{p,q}\,\delta_{S_p \neq S_q} + \lambda \sum R_p(S_p) \tag{3.15}$$

where S_p and S_q can take the label values {liver or background} in order to find the minimum of E and the corresponding optimal set of segmentation S_p of all voxels. Cost function E and edge weights $w_{p,q}$ were used for the second run of the graph-cut technique, while the region term weights R_p were redefined as follows:

$$R_p(tumor) = \frac{\exp\frac{-(I_P-\mu_{tumor})^2}{2\,\sigma_{tumor}^2}}{\sigma_{tumor}\sqrt{2\pi}} \tag{3.16}$$

$$R_p(liver) = \frac{\exp\frac{-(I_P-\mu_{liver})^2}{2\,\sigma_{liver}^2}}{\sigma_{liver}\sqrt{2\pi}} \tag{3.17}$$

Geodesic distances and edge information can be combined in a Graph cut optimization framework, and can be used for predicted classification accuracy from the inferred color models to automatically tune the tradeoff between the strengths and weaknesses of the two.

The energy function relies on two main terms: i) a region term (penalties depending on neighborhood context and on voxel labeling) and ii) a boundary term (penalties based on adjacent voxels dissimilarity). Thus the Graph-Cut Technique solutions avoid local minima, providing numerical robustness and do not use any shape-prior characteristics that would constrain too strongly recoverable shapes. It produces better segmentation results than other fully automatic methods found in literature in both terms of accuracy and time processing. The image segmentation methods may be classified into several types:

1) Image-based methods,
2) Model-based methods, and
3) Hybrid methods.

Purely image-based methods perform segmentation based only on information available in the image; these include thresholding, region growing, morphological operations [13], active contours, level sets[18], live wire (LW)[9], watershed, fuzzy connectedness[23], and graph cuts (GCs) [5],[15],[17],[24],[25]. These methods perform well on high-quality images.

Demerit: However, the results are not as good when the image quality is inferior or boundary information is missing.

Model-based methods employ object population shape and appearance priors such as atlases, statistical active shape models [15], deformable templates [3] and statistical active appearance models (AAMs) [16],[23].

Merit: When some object information is missing, such gaps can be filled by drawing upon the prior information present in the model.

Hybrid methods [11], [12] that form a combination of two more approaches are emerging as powerful segmentation tools. The synergy that exists between these two approaches, i.e., purely image-based and model-based strategies is called as hybrid methods.

Merit: Hybrid approach can achieve a result much quicker with greater accuracy.

Most of the image-based [20], model-based [19], and even hybrid segmentation [11] techniques are often tailored for specific body regions (brain, abdomen, etc.) and different image modalities (CT, MRI, etc.). However, it is desirable to generalize image segmentation methodologies for any (or most) body regions and different image modalities and protocols. Furthermore, it is desirable for an image segmentation algorithm not to heavily depend upon the characteristics of fixed shape families and different image modalities. While perhaps some of the above techniques can be generalized in this spirit, few methods have demonstrated to work in this general setting. Existing Methods

IV. RESULTS AND DISCUSSION

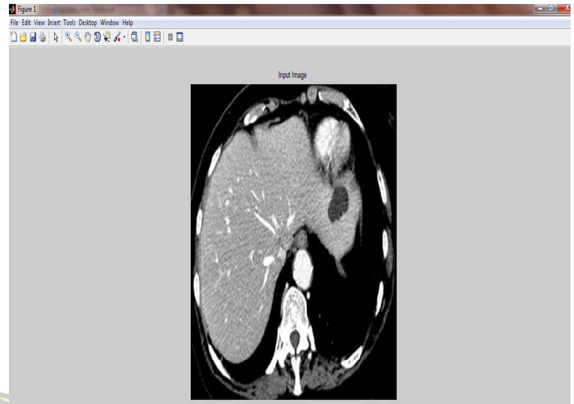

Fig.2. Input Image for Performance Evaluation

Fig.2. shows the input image considered for performance evaluation

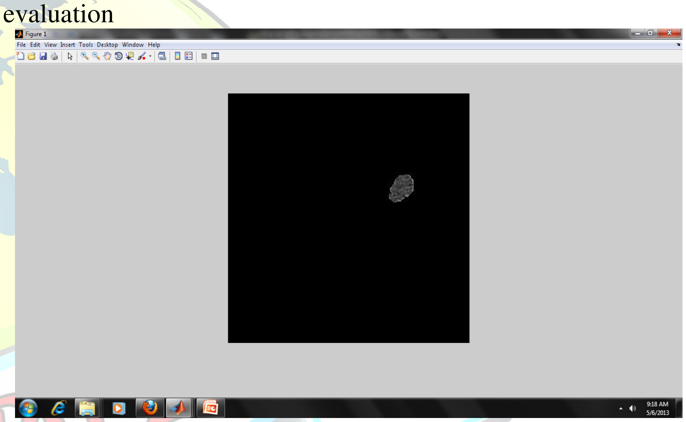

Fig.3. Ground Truth Image for Performance Evaluation

Fig.3. shows the Ground Truth image obtained by Live wire method which is considered as the original image.

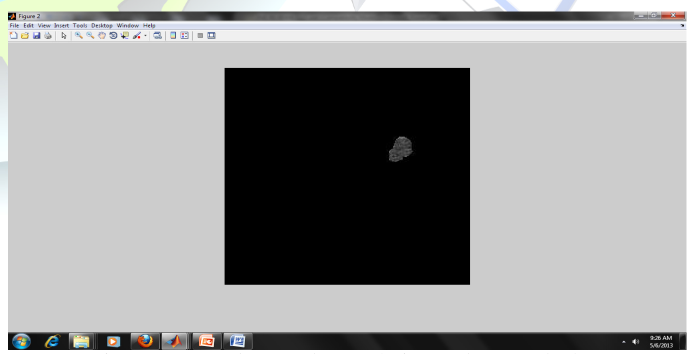

Fig.4. Segmented Tumor by Geodesic Graph cut method

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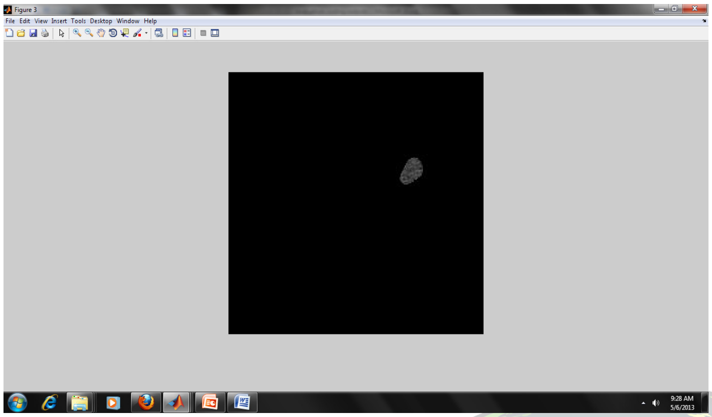

Fig.5. Segmented Tumor by Graph cut method

Fig.5. shows the Segmented tumor image obtained using Graph cut method

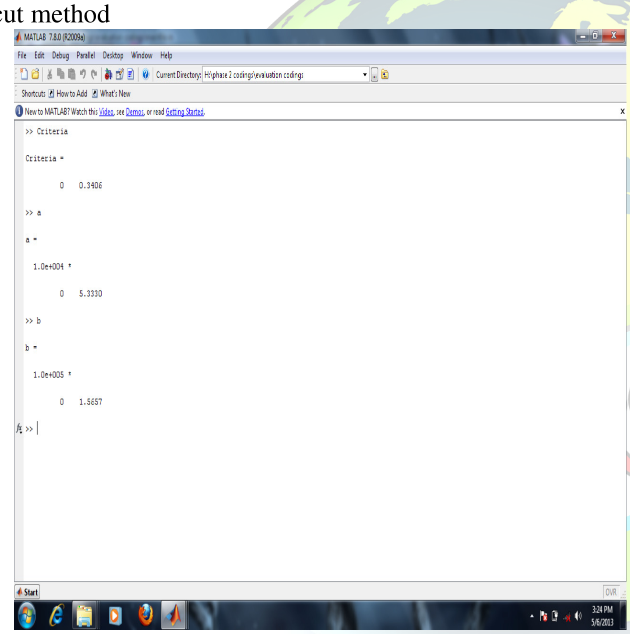

Fig.6. Evaluation of Efficiency of two methods

Fig.6. shows the performance evaluation of Geodesic Graph cut method and Graph cut method. Parameter 'Criteria' corresponds to the Ground truth or the original image. Parameter 'a' corresponds to Similarity coefficient of Geodesic Graph cut method and parameter 'b' corresponds to Similarity coefficient of Graph cut method. From the figure, it is observed that Geodesic Graph Cut method has obtained a larger value in terms of Similarity Coefficient than Graph cut method.

Fig.7. Different sets of Input images for Objective Image Fusion Performance

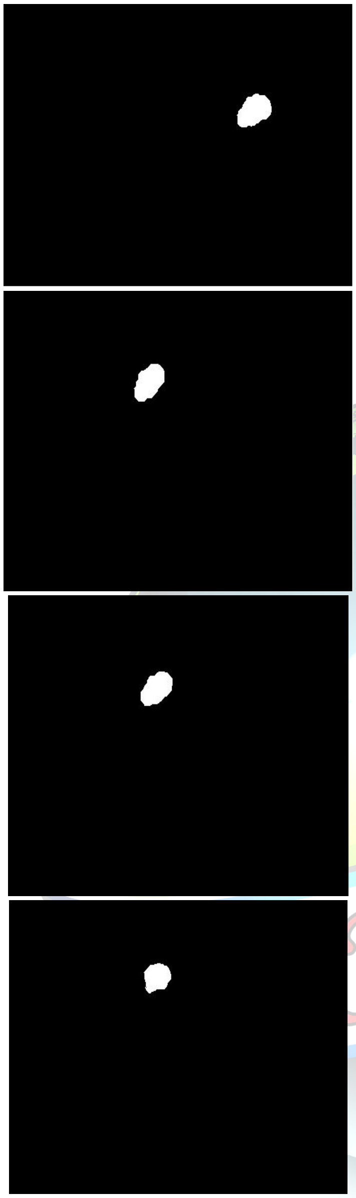

Fig.8. Different Data Sets of Ground Truth Images

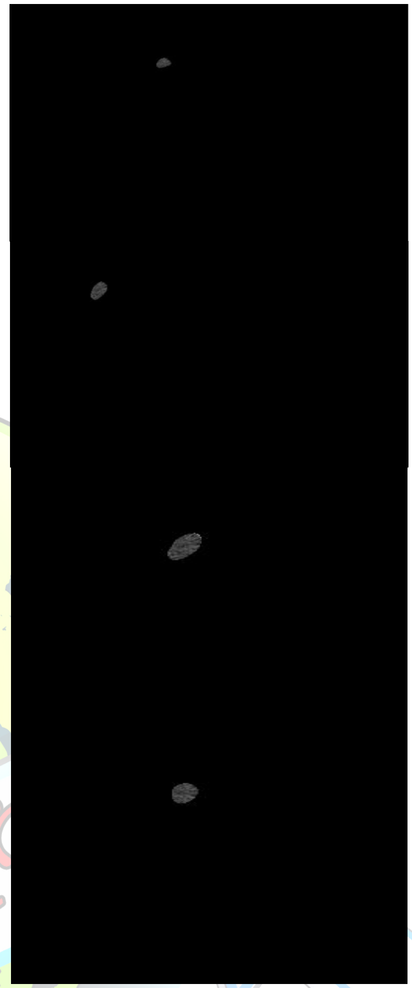

Fig.9. Segmented Image Sets by Geodesic Graph cut Approach

Fig.8. shows different data sets of Ground Truth Images for Objective Image Fusion Performance.

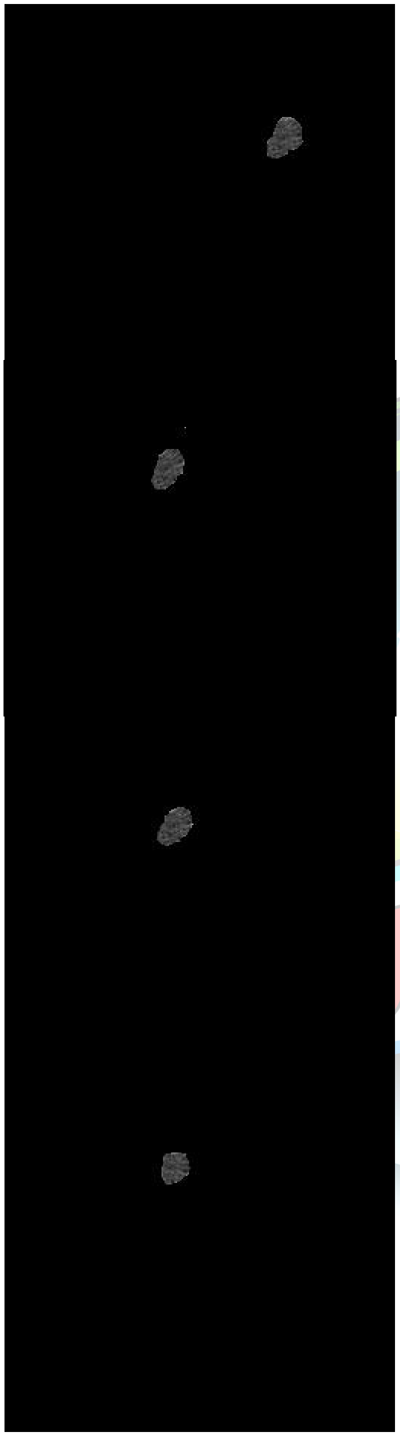

Fig.10. Segmented Image Sets by Graph cut Approach

Objective Image Fusion technique helps to evaluate the performance of the two methods effectively. The goal in pixel level image fusion is to combine and preserve in a single output image all the "important" visual information that is present in a number of input images. The objective fusion measure should i) extract all the perceptually important information that exists in the input images and ii) measure the ability of the fusion process to transfer as accurately as possible this information into the output image. In order to establish the subjective relevance of the proposed methodology in assessing the performance of pixel level fusion systems, $Q_P^{AB/F}$ was estimated in relation to three fusion algorithms.

The first, Scheme I, is a conventional multi resolution fusion system that employs an "area" type sub band pixel selection approach during pyramid fusion. Scheme II employs the same conventional Quadrature Mirror Filter (QMF) decomposition approach with an advanced cross band selection technique for pyramid fusion. Scheme III is a computationally efficient system based on a background/foreground decomposition and fusion process. Thus informal subjective tests were performed using pairs of input images and the corresponding fused output images produced by two different fusion algorithms. A preference for a particular fused image assigned one point to the system used to produce it, whereas half a point was given to both systems in the case of equal preference. An average Subjective Score (SS) was therefore obtained for each fusion system, using the above hard decision process.

The same hard decision preference and corresponding point allocation was also employed using the $Q_P^{AB/F}$ objective measure. That is, for a particular input pair:

$Q_I^{AB/F} > Q_{II}^{AB/F}$, 1 point assigned to Scheme I

$Q_I^{AB/F} < Q_{II}^{AB/F}$, 1 point assigned to Scheme II

$Q_I^{AB/F} = Q_{II}^{AB/F}$, ½ point assigned to both Scheme I and Scheme II

This process yielded an average Objective Score (OS).

Graph Cut and Geodesic Graph-cut algorithms produced a liver volume with a high level of overlapping given by an average DSC of 96.17% ± 0.87 and of 95.49 ± 0.66, respectively. Graph Cuts reached therefore a slightly better average DSC, but on nine cases over 25 (36%) Geodesic Graph-cuts produced a liver surface segmentation with a higher DSC than Graph cuts method. FPR and FNR misclassification ratios were balanced with contemporary low values for both automatic approaches. The algorithm based on Graph cuts method generated fairly equal false alarm rate (FPR = 3.35% ± 1.19) and undetection rate (FNR = 3.87± 0.98). In addition, over the set of 25 cases, the average Distance – Error was equal to 2.38mm ±0.41for Graph cuts method, while it was fairly better for Geodesic

Graph-cut method with a value of 2.19 mm ± 0.59. Table 4.2. shows the Comparison of Liver Surface Segmentation techniques.

Among the 52 hepatic tumors diagnosed in 25 patients, Geodesic Graph-cut algorithm detected 48 tumors leading to a detection rate of 92.31%, while Graph cut method only detected 44 tumors for a detection rate of 84.62%. The differences between results produced by the two automatic algorithms were emphasized by three metrics as indicated in Table 4.3. Regarding the volume overlapping of hepatic tumors, Geodesic Graph-cut algorithm provided an average DSC of 88.65% ± 3.01, while Graph cut method reached a lower average DSC equal to 87.10% ± 2.99. In terms of misclassification, Geodesic Graph-cut algorithm presented again a lower average FPR than Graph Cut method (6.10% ± 2.52 versus 8.99% ± 3.95). However, the undetection rate was in favor of Graph cuts method since its average FNR reached the value of 8.97% ± 2.26, while Geodesic Graph-cuts obtained an average FNR of 9.89% ± 2.93.

Both algorithms were run on a personal computer with 3.4 GHz CPU speed and 1 Gbyte of random-access memory. The indicated values are the average time needed for a single slice; these ones are normalized on the number of slices for each specific processed dataset. The Geodesic Graph-cut algorithm always produced faster segmentation than Graph cut algorithm with an average processing time per slice equal to 10.9 s ± 1.1 and 11.5 s ± 1.1, respectively. Into these time values, mean shift filtering operation is included and represents most part of the required time, since it is equal to an average of 7.3 s ± 1.1 (Table 4.4).

Other preprocessing filters (convolution, median, or average filter, etc.) were assessed but segmentation results were not acceptable in view of the objective of this study: fully automatic process, accurate liver, and tumors extractions.

Among the 52 hepatic tumors diagnosed in 25 patients, Geodesic Graph-cut algorithm detected 48 tumors leading to a detection rate of 92.31%, while Graph cut method only detected 44 tumors for a detection rate of 84.62%. Automatic liver segmentation by the Geodesic Graph-cut algorithm succeeds to include the tumors (underneath the surface) inside the liver segmentation. The reason is that the Geodesic Graph-cuts include neighboring contextual information enabling to overstep edges between tumors or vessel and liver parenchyma.

Both automatic techniques provided highly accurate liver surface segmentation with respect to ground truth image defined as the gold standard. Indeed, both algorithms reached quite similar good values for all comparative metrics.

V. CONCLUSION

Automatic Initialization method is based on Statistical model distribution of liver average intensity and Standard deviation. Tumor segmentation required also the same automatic initialization as that of the liver. This step was applied only to liver volume, obtained after automatic delineation of liver surface: this latter, applied to original dataset volume, was used as a mask in order to prevent processing overloads and avoid errors related to the presence of surrounding tissues presenting similar gray scale distributions. Additionally, for this purpose, the voxels belonging to the intensity range domain were also removed from the segmented liver volume. This choice allowed the correct identification of liver respect to other organs, optimizing the calculation resources and increasing the tumor segmentation accuracy.

REFERENCES

[1] Abdel-massieh.N.H., Hadhoud.M.M., and Moustafa.K.A.,(2010) “A fully automatic and efficient technique for liver segmentation from abdominal CT images,” in Proc. 7th Int. Conf. Inform. Syst. (INFOS),pp. 1–8.

[2] Ben-Dan.I. and Shenhav.E.,(2008) “Liver Tumor segmentation in CT images using probabilistic methods,” in Proc. 11th Int. Conf. Med. Image Comput. Comput. Assisted Intervention, MICCAI’08,, New York, pp. 1–11.

[3] Boykov.Y. and Kolmogorov.V.,(2003) “Computing geodesics and minimal surfaces via graph-cuts,” in Proc. 4th Int. Conf. Comput. Vision, Nice,pp. 26–33

[4] Grady.L.(2006) Random walks for image segmentation. IEEE Trans.PAMI, 28(11):1768–1783.vol.16, pp. 550-575

[5] Lim.S.J., Jeong.Y.Y., and Ho.Y.S.,(2006) “Automatic liver segmentation for volume measurement in CT images,” J Vis. Commun. Image Represent., vol. 17, pp. 860–875.

[6] Guillermo Sapiro.G.(2007) “A geodesic framework for fast interactive image and video segmentation and matting”. IEEE ICCV 2007, pages 1–8.

[7] Malcolm.J., Rathi.Y., and Tannenbaum.A.(2007) A graph cut approach to image segmentation in tensor space. In IEEE CVPR, pages 50-65.

