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An Enhanced Approach for Segmentation of Liver from Computed Tomography Images

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An accurate segmentation of liver from Computed Tomography (CT) scans is essential for liver tumor research as it offers valuable information for clinical diagnosis and treatment. However, it is challenging to achieve an accurate segmentation of the liver because of the blurred edges, low contrast and similar intensity of the organs in the CT scan. In this paper, an automated model which will segment the liver from CT images using a hybrid algorithm has been used. The segmentation of liver from CT scan is done with the help of Particle Swarm Optimization (PSO) followed by level set algorithm. The ultimate aim of using this hybrid algorithm is to improve the accuracy of liver segmentation. Computer aided classification of liver CT into healthy and tumorous images aids in diagnosis of liver diseases. It can help a great deal in diagnosis of liver disorders. In order to achieve better classification results, it is of high importance to segment the liver accurately without an error of over or under segmentation. The results obtained indicate that the approach used in this work is faster and has 98.62% accuracy, 99.2% specificity, 97.1% sensitivity, 97.8% F-measure, 96.6% Matthews Coefficient Constant (MCC), 99.08% precision, 97.8% dice coefficient and 95.7% jaccard coefficient in segmenting the liver.

Keywords: Evaluation parameters, Hybrid approach, Image segmentation, Level set, Liver segmentation, PSO

Introduction

Liver is a reddish brown color organ. It is placed in the upper right spot of the midriffs.[1] Hepatocellular carcinoma by and large is categorized as initial liver cancer and non-primary liver cancer. The initial stages of liver cancer denote results in the formation of cancer cells whereas the non-primary or secondary indicates the proliferation of cancer cells into another organ of the human anatomy.[2] Hepatocellular carcinoma is the most common type of liver cancer. It is the typical form of liver cancer that arises in people mostly with chronic hepatitis B and C. This diagnostically relevant imaging approach assists clinicians to find the disorders and makes certain that the determination is precised.

These techniques include Magnetic Resonance (MR) imaging, Computed Tomography (CT) and X-ray. Among these, CT scan is the most dedicated procedure that provides to the radiologist about the exact scenario of the hepatic cancer.[3] So, this paper proposes an approach that combines the eminence of the PSO algorithm and level set algorithm. This is exercised in order to obtain better result irrespective of the complexity of the hepatic organ.[4]

This method incorporates the transformation that is defined on a gray scale[5] along with the optimization of a problem. The optimization is done by periodically attempting to boost the candidate solution with respect to given computation of caliber of the liver disorder.

The level set is a balloon force approach. Here the region grows based on the initial seed point and the liver region is marked. This observation is hybridized with the method called PSO where all the particles converge to a point in the search space. The reason for adopting PSO is that it is an uncomplicated implementation with high robustness in controlling the parameters that are involved when compared with other heuristic approaches. The choice of the PSO parameters influences the optimization performance. It gives the radiologist a clear view of the hepatic organ to get into a conclusion about the cancerous images.

Related Work

Nanda *et al.*[6] proposed the means of segmentation of liver which makes use of the convolutional neural

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network. Firstly, the liver region of interest (ROI) is extorted. The outcome of the ROI is then allowed to flow into the second network. In this modus two CNN architectures ultimately U-Net and SEG –Net have been explored in order to set out the liver segmentation together with the lesions. Besides the incorporation of the cascaded architecture an Artificial Neural Network (ANN) is also exerted which is used for tumour detection in the ROI output. This method is further made efficacious by adopting the Laws' Texture energy in which texture characteristics and its fine arena are acquired on the liver segmented image and get utilized in the tumour detector. Moreover, this architecture and the highly intensified parameters of the ANN classifier are entirely leveraged with the backing of the genetic algorithm. It is perceived that SEG- Net surpasses the U Net in the liver extrication with the towering DICE score of 0.95557. On the flip slide U Net attains the propitious execution in the lesion segmentation that achieves 0.6979 DICE score against 0.5198 for SEG-Net. It is deduced that SEG- Net attains better results when proportionately massive and specified datum are exercised. Consequently, in the lesion segmentation the U Net architecture outperforms when meagre amount of dataset on the tumour ridden livers are employed.

Satapathy *et al.*[7] proposed the optimization technique that evolved from the population bases called socio group optimization influenced from the perception of social behavior of human in heading towards resolving a complex task. This SGO procedure is branched into two parts that comprise of "improving phase" and "acquiring phase". In the improving phase the knowledge or proficiency level of each and every individual is reinforced with the impact of the best person in that group. The best person in the group is the one holding the highest level of knowledge and potential to decode the problem. In SGO the best person is the best solution. And in the acquiring phase each person enhances their knowledge with the mutual influence of the other person in the group and also the best person in the group at that point in time. In this optimization the number of functional evaluations (FE's) is picked up in order to collate the speed of the other algorithms as a measure of the computation time rather than selecting the generations and iterations. To assess the efficacy of SGO, extensive experiments are administered on number of multifarious unconstrained benchmark functions taken from the IEEE congress on Evolutionary computation 2005 competition.

Esneault *et al.*[8] have proposed a methodology for segmentation of the liver that comprises advantages of both the application of classical graph cut and 3-dimension geometrical moment tubular structures. This fusion strategy involves local modelling of vessels, their perimeter and local orientations. This model is further inculcated from a localized restraint into a graph cut algorithm that encompasses the section of the graphs into sub graphs by a minimum cut or maximum flow algorithm where the final segmentation of the input liver image is imparted. This vessel model designates the class vessel and class background as the source and sinks respectively. This model entirely relies on real coronary artery tree description. This model takes branching off into account and exhibits good tree tracking. It also results in accurate vessel diameter estimation. Moreover, it excludes the dwindling bias on enlarged anatomy.

Xu *et al.*[9] have proposed a liver segmentation procedure that includes an image pre-processing scheme, a region growing and a novel enhanced liver segmentation method which are constructed on active contour model in addition to a new signed force function. These semi-automatic techniques consist of three strides. Firstly, the original input pictures are pre-processed by a sequence of methods to extricate the binary hepatic input images. Then, some seed points are fixed on the binary image for the surface to get the preliminary contour of the hepatic organ. In the first stride the gradient immensity of hepatic images is leveled up by Gaussian function to put down the unwanted noise and magnify the edges. Furthermore, a binarization strategy is initiated on the fundamentals of the gradient data of images in order to automatically choose the favorable boundary without artificially setting perimeter. In the third stride, a signed pressure functional is extended which could assimilate both localized and broad details as well as ration out the local and global proportions in a mechanized way which relies on the image of the gradient data. They have used two public datasets SLIVER07, 3Dircadb to effectively evaluate the method.

Elaziz *et al.*[10] have proposed a smart image segmentation technique called multilevel thresholding in order to choose the appropriate optimal estimator, a hybrid meta heuristic method which is inculcated through the swarm selectioning. The selected swarm algorithms are exercised together in a series to apprehend the optimal values that augment the Otsu function which is a discrete 1-D analog. This excludes its limitation of hefty reckoning and preterm confluences.

Li *et al*.[11] have proposed a modification of the indigenous U-Net that encompasses dense module, inception module and dilated convolution in the encoding path for fine data flow and wide receptive field. These bottleneck elements are supervised (BS) U-Net with further supervision on the bottleneck characteristics vector which holds huge condensed low dimensional information of labeling maps, that aids in lessening of information dropping. BSU-Net executes the process in a superior way than all the prevailing 2-D network.

Liu *et al*.[12] have proposed a mechanism of hepatic CT sequence image segmentation algorithm named GIU-Net which fuses a revamped U-Net neural network framework with graph cutting model. This overcomes the flaws in the CT image noise and the vast disparity in the configuration of the hepatic organ of the victims. A probability distribution map of a liver section is acquired by obtaining the image pre segmentation with an upgraded U-Net and then the graph cut energy is cobbled up from the delineated distribution which is obtained with the image series. Indicatively U-Net is remodeled by instantly emulating the features of the emphasized layer into more précised secure semantic features.

Ranjbarzadeh *et al*.[13] have proposed a nexus that includes the modus of concave and convex points which is labelled with mean shift and FCM clustering, an unsupervised data split approach to study the hepatic lump. They have extracted Organ's edges by employing the kirsch filter. The concave and convex spotting is eventually enumerated by gyrating the kirsch mask for about 45 degrees in the octonary prime compass direction. All contour portions are represented as an ellipse and processed in several proceedings. The mean shift algorithm has been engrossed to make the images more consistent along with the targeted structure and to intensify the contrast of the definite borders in an image with minimal discrepancy. Ultimately the liver bounds and tumours are acquired in a desired form using FCM algorithm.

Krishnan *et al*.[14] have proposed a computer oriented proposal to assort ten disparate focal and spread out hepatic ailments by manipulating the ultrasound images. Active contour segmentation process is exerted to alienate the contaminated fragment from the ultrasound images. Wavelet which is transformed into a small mathematical function is employed on the segmented section that induces horizontal, vertical, diagonal wavelet to outstrip the gleam and incongruity. This eventually contributes to the expansion of the ultrasound images. From this wavelet filtered images grey level run length matrix features are drawn out and stratified using a tenfold cross validation scheme. They have compared the results obtained against those obtained using spatial feature extraction techniques. It imparts a comprehensive classification veracity of about 91% for a coalition of ten classes of analogous looking lurgy liver which is more notable than the spatial domain.

These existing techniques have some disadvantages in segmenting the liver efficiently. This paper proposes an optimized level set hybrid algorithm to segment the liver and it has resulted in a relatively high performance.

Materials and Methods

Proposed Work

The proposed work is used to detect the liver automatically from CT scans. This technique needs abdomen CT images as an input. The architecture of proposed work is illustrated in Fig. 1. With the help of hybrid approach, good segmentation results can be achieved in segmenting the liver from the CT image. Then the level set algorithm is applied on the output of the PSO image to segment the liver. This approach aids in segmenting the hepatic organ without any bias.

Particle Swarm Optimization

PSO generates a school of particles which advance in the space in and around the tissues and probe into their goal.[15] The place that goes with their demand is specified by a fitness function. PSO adopts a batch of agents which accounts for the swarm moving around the search space gazing for the optimal solution. Each and every particle in the exploring space is

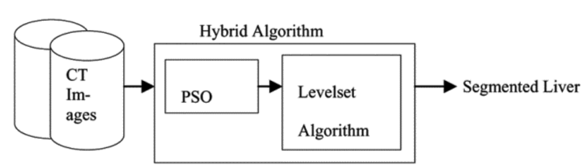

Fig. 1 — Architecture of the hybrid system

customized by its flying pattern in accordance with its own flying experience that is encountered in its path. Also it regulates its advancing momentum aggressively with respect to the path record of its own and for its fellow swarm. The analogy of birds is usually discovering the optimum place to rest. The best place is an incorporation of easy accessibility to all needy nourishments and water. In PSO, every single solution is a "bird" or a "particle" in the search space. All the particles possess the fitness values that are estimated by the fitness function and exhibit the velocities that coordinate the particle flying direction. The particle flies all over the problem span that heeds with the topical optimum particles. PSO is propelled with a cluster of random particles generally referred to as solutions and then looks for optima by rationalizing the generation. Each particle is reformed by tracing two optimal values in every iteration. The first value is called pbest and also regarded as the fitness value. Another optimum value is trajected by the particle swarm chooser. This particle swarm optimizer is the best value that is extracted by any particle in the given clusters. This optimum value is "global best" and it is called gbest. After finding the two best values, the particle updates its velocity and positions as illustrated by Eqs (1) and (2).

v[] = v[] + c1 * rand() * (pbest[] - present[]) + c2 * rand() * (gbest[] - present[]) … (1)

present[] = present[] + v[] … (2)

The particle velocity is v[], and the current particle is present[] (solution). As previously stated, pbest[] and gbest[] are defined. rand () is a number that is generated at random (0,1). Learning variables c1 and c2.

The intensity levels of nearby organs and the liver are so similar in a CT scan, segmenting the liver is the most difficult component of the application. Hence, the PSO technique is used to maximize the value of fitness criteria of the CT image to segment the accurate liver. This is the most crucial step, since any under or over segmentation will result in a portion or all of the tumours being missed.

Let S denote the number of particles in the swarm, each with a position in the search space of $xi \in R^n$ and a velocity of $vi \in R^n$. Let pi represent the best-known position of particle I and g represent the best-known position of the entire swarm. A basic PSO algorithm is then

Algorithm 1: PSO Algorithm
Input: Abdomen CT image
Output: Optimized CT image
for each particle i=1,…, S do
assign the position of the particle $\mathbf{x}_i \sim U(\mathbf{b_{lo}}, \mathbf{b_{up}})$
assign the best position of the particle $\mathbf{p}_i \leftarrow \mathbf{x}_i$
if $f(\mathbf{p}_i) < f(\mathbf{g})$ **then**
update swarm's best position $\mathbf{g} \leftarrow \mathbf{p}_i$
assign velocity of particle: $\mathbf{v}_i \sim U(-|\mathbf{b_{up}}-\mathbf{b_{lo}}|, |\mathbf{b_{up}}-\mathbf{b_{lo}}|)$
while a stopping criterion is not met **do**
for each particle i = 1, ..., S **do**
for each dimension d = 1, ..., n **do**
select random numbers: $r_p, r_g \sim U(0,1)$
Update velocity of particle: $\mathbf{v}_{i,d} \leftarrow \omega\ \mathbf{v}_{i,d} + \varphi_p r_p (\mathbf{p}_{i,d}-\mathbf{x}_{i,d}) + \varphi_g r_g (\mathbf{g}_d-\mathbf{x}_{i,d})$
Update the position of particle: $\mathbf{x}_i \leftarrow \mathbf{x}_i + \mathbf{v}_i$
if $f(\mathbf{x}_i) < f(\mathbf{p}_i)$ **then**
Update the best position: $\mathbf{p}_i \leftarrow \mathbf{x}_i$
if $f(\mathbf{p}_i) < f(\mathbf{g})$ **then**
Update the swarm's best known position: g←pi

The variables b_{lo} and b_{up} reflect the search space of lower boundary and upper boundary respectively. The number of iterations completed or a solution that finds the appropriate objective function value can be used as the termination criterion. The practitioner chooses the parameters ω, φ_p, and φ_g which regulate the PSO method's behaviour and efficacy. lr represents the learning rate ($0 \leq lr \leq 1.0$), which is the proportion at which the velocity affects the movement of the particle.

Tuning of local best, neighborhood best and global best parameters are important to get the good results. These parameters are assigned the worst possible values that can be taken into consideration depending on the application and characteristics of the problem.

Level set Algorithm

The level set method is applied[16] for medical imaging purposes. The idea behind the level set method is to incorporate a curve within a surface. Curve evaluation theory forms the basis of the level set method that adopts the probability distribution equation to write the deformation curve. Level pair surface is adopted to extract the geometrical properties of the contour which are noted merits of the level set approach. Active contours are represented implicitly in this approach in the zero level set of a greater dimensionality function. It exhibits the evolving contour more precisely by using the parametric equation. This leads to fine managing of the topological changes that occur in this method. Edge based model and region based model are the two prevailing level set methods. In this work, an edge based active contour model has been included and the directional evolution is handled efficiently by a balloon force. This force excludes the under or over segmentation flaws which are quite common in the segmentation of the liver because of the similar intensity of an adjacent organ.

Results and Discussion

The Fig. 2 represents an abdomen input CT image. PSO algorithm is applied on that input image. The output of PSO for the sample input given in Fig. 2 is shown in Fig. 3. This PSO output is applied to the level set algorithm for segmenting liver region. During this process, the liver region is marked in red colour based on the initial contour as represented in Fig. 4. The segmented liver image and the ground truth of the input image are shown in Fig. 5 and Fig. 6 respectively.

The below Table 1 shows the various evaluation parameters, namely, accuracy, sensitivity, F-measure,

Fig. 2 — Abdomen CT input image

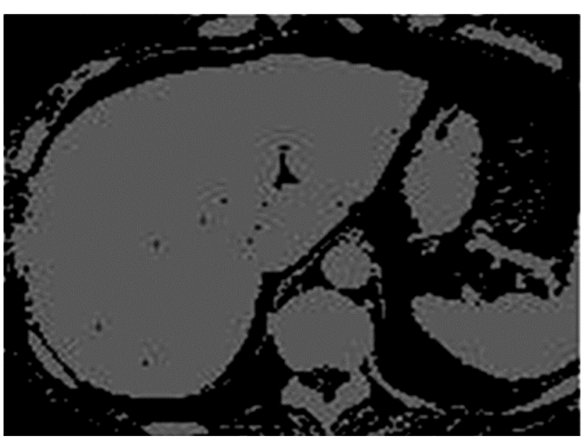

Fig. 3 — Output of PSO

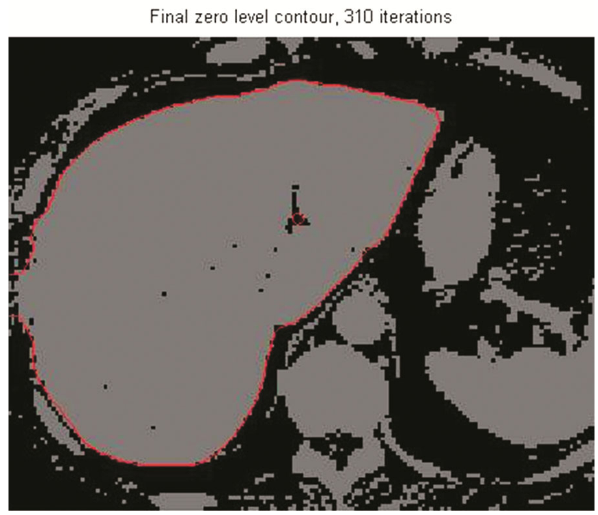

Fig. 4 — Level set applied on the image shown in Fig 3

Fig. 5 — Segmented Liver

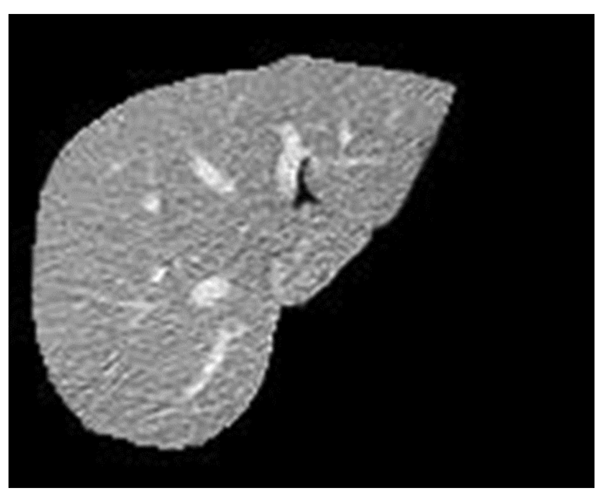

Fig. 6 — Ground Truth

Table 1 — Performance measures using Hybrid approach

Image	Accuracy	Sensitivity	F-measure	Specificity	Precision	MCC	Dice	Jaccard
1	0.9845	0.9710	0.9782	0.9921	0.9855	0.9663	0.9782	0.9573
2	0.9135	0.6058	0.7519	0.9985	0.9908	0.7344	0.7519	0.6024
3	0.9669	0.8853	0.9236	0.9908	0.9654	0.9039	0.9236	0.8580
4	0.9661	0.8781	0.9197	0.9911	0.9655	0.8999	0.9197	0.8514
5	0.9862	0.9593	0.9697	0.9942	0.9803	0.9608	0.9697	0.9412

Table 2 — Performance measures using level set without PSO approach

Image	Accuracy	Sensitivity	F-measure	Specificity	Precision	MCC	Dice	Jaccard
1	0.8330	0.9838	0.6928	0.7973	0.5346	0.6433	0.6928	0.5300
2	0.8603	0.1139	0.0154	0.8675	0.0082	0.0054	0.0154	0.0077
3	0.9030	0.8820	0.7234	0.9065	0.6131	0.7234	0.7234	0.5666
4	0.8416	0.8542	0.3949	0.8408	0.2568	0.3949	0.3949	0.2460
5	0.7959	0.9845	0.1748	0.7916	0.0959	0.1748	0.1748	0.0958

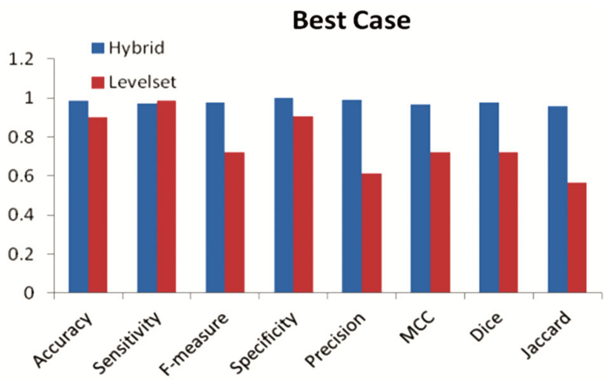

Fig. 7 — Best case graph

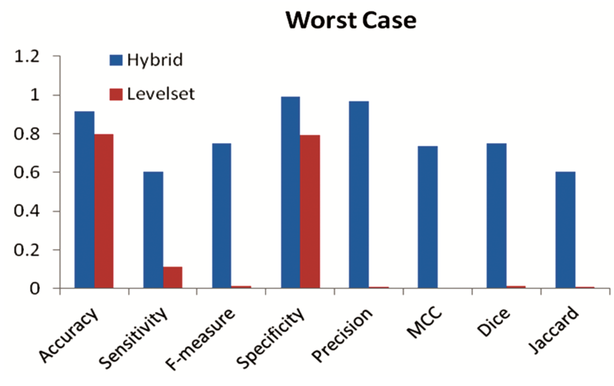

Fig. 8 — Worst case graph

specificity, precision, Matthews Correlation Coefficient (MCC), dice co-efficient and jaccard similarity coefficient achieved using the hybrid approach. Similarly, Table 2 shows the evaluation parameters calculated for the segmented liver image using level set algorithm.

Eqs (3) - (10) are used to calculate the evaluation parameters.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad \dots (3)$$

$$Sensitivity = \frac{TP}{TP+FN} \quad \dots (4)$$

$$Precision = \frac{TP}{TP+FP} \quad \dots (5)$$

$$F-Measure = \frac{2TP}{2TP+FP+FN} \quad \dots (6)$$

$$MCC = \frac{(TP*TN)-(FP*FN)}{\sqrt{(TP+FP)*(TP+FN)*(TN+FP)*(TN+FN)}} \quad \dots (7)$$

$$Specificity = \frac{TN}{TN+FP} \quad \dots (8)$$

$$DiceCoefficient = \frac{2TP}{2TP+FN+FP} \quad \dots (9)$$

$$JaccardCoefficient = \frac{Dice}{2-Dice} \quad \dots (10)$$

The above Figs 7 – 9 represents the best, worst and the average cases of hybrid and level set approaches, respectively.

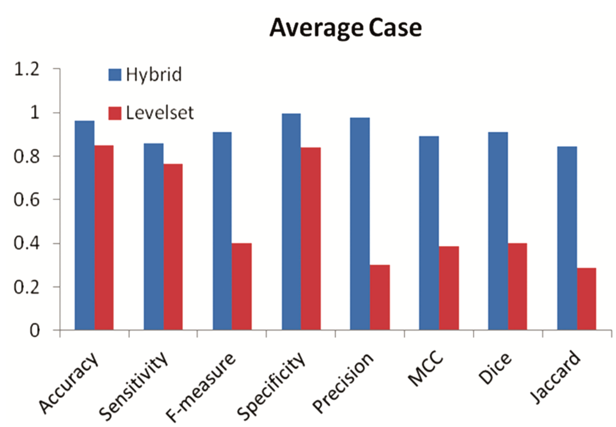

Fig. 9 — Average case graph

Conclusions

This paper has undertaken an approach considering the critical issues that are daunting in the domain. In this work, to segment the liver from CT images, the combination of PSO and levelset algorithm has been used. This framework has been designed in such a way that it is simple to put into practice. When evaluated across multiple datasets, the results are fairly stable. The proposed work's evaluation parameter is as excellent as the existing systems, according to experimental data. A better approach could be built in the future, which would lower error rates even further and increase detection possibilities. This proposed work can also be extended to 3D images as well as images obtained from various medical imaging modalities such as MRI and Ultrasound.

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Conflicts of Interest

The authors state that they have no conflicts of interests to disclose in relation to this research.

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