Optimized Liver Tumor Detection and Segmentation Using Neural Network

Akanksha Sharma, Parminder Kaur

Abstract - Image processing has become an essential component in many fields of biomedical research such as tumor detection, automatically determining the volume of a heart chamber, screening lung scans for possible diseases. Different techniques for automatic detection of liver tumor involve various steps: image acquisition, segmentation, classification using neural network and optimization, and identification of tumor type. Most common segmentation approaches are: Region based, Threshold based, Level set, Clustering based and Edge detection. Liver tumor segmentation is done with region based approach in this research work. Region based methods partition an image into regions that are similar according to a set of predefined criteria where as other segmentation approaches like edge detection methods partition an image according to rapid changes in intensity near the edges. In this research work Particle Swarm Optimization (PSO) and Seeker Optimization algorithm (SOA) have been compared for classification of tumor using CT scan images. The main focus of this work is to detect liver tumor and compare results of PSO and SOA in term of detection and classification accuracy and elapsed time. Region based segmentation approach has been used for segmentation of liver and liver tumor from CT scan images. PSO and SOA are used for classification and PSO optimization gives better results in term of detection and classification accuracy and elapsed time. For liver tumor classification, PSO results with as 93.3% detection and classification accuracy where as SOA results in 60% detection and classification accuracy.

Keywords— Particle Swarm Optimization (PSO), Seeker Optimization algorithm (SOA), hepatocellular carcinoma (HCC), Benign (hemangioma), Metastasized.

I. INTRODUCTION

The body is made up of trillions of living cells. Normal body cells grow, divide into new cells, and die in an orderly fashion. Cancer begins when cells in a part of the body start to grow out of control. There are many kinds of cancer, but they all start because of out-of-control growth of abnormal cells [1].

Liver cancer is the fifth most common cancer in men and the seventh in women. The regions of high incidence are Eastern and South-Eastern Asia, Middle and Western Africa. Low rates are estimated in developed regions, with the exception of Southern Europe where the incidence in men is significantly higher than in other developed regions [2]. The liver is the largest gland and largest internal organ in the human body.

Liver a meaty organ that sits on the right side of the belly just beneath on right lung. Weighing 3 pounds or 1.4-1.6 kg, the liver is a dark red, wedge-shaped gland approximately eight and a half inches long.

It is shaped like a pyramid and divided into right and left lobes. Approximately 1.5 L of blood flows through the liver each minute. The liver holds about 13% of the body's blood supply. Liver gets blood from two sources: the hepatic artery supplies the liver with blood rich in oxygen from the heart, and the portal vein brings nutrient-rich blood from the intestines. Blood that has circulated through the stomach, spleen, and intestine enters the liver through the portal vein as part of the portal circulation system. The liver extracts nutrients and toxins from this blood, which is then returned through the hepatic vein to the right side of the heart. The hepatic artery supplies oxygenated blood directly from the heart to the liver.

An estimated 30,640 new cases of liver cancer (including intra hepatic bile duct cancers) are expected to occur in the US during 2013. More than 80% of these cases are hepatocellular carcinoma (HCC), originating from hepatocytes, the predominant liver cell type. Liver cancer incidence rates are three times higher in men than in women. From 2005 to 2009, rates increased by 3.7% per year in men and by 3.0% per year in women**.** The total utilization rate of diagnosis by imaging grew at a compound annual growth rate of 4.1% from 1998 to 2005, but this decreased to 1.4% from 2005 to 2008. From 2005 through 2008, the overall growth trends flattened dramatically for MRI and nuclear medicine and abated somewhat for CT, ultrasound, and echocardiography.

A national representative survey on cancer mortality in India conducted by Rajesh Dikshit, Prakash Gupta et al [3] estimated indirectly that about 635000 people died from cancer in 2008, representing about 8% of all estimated global cancer deaths and about 6% of all deaths in India.

II. METHODOLOGY

For optimized liver tumor detection first of all load the CT scan image of the patient. This CT scan image is then processed for removal of noise. Further the image is enhanced to get better quality image for tumor detection. Next step is segmentation process.

Segmentation is done in this work with ROI approach. Segmentation separates out the liver from abdomen and tumor from liver. Optimization algorithms: PSO and SOA are used to train the neurons for extracting the type of tumor. Flow chart for optimized liver tumor detector is shown in figure below:

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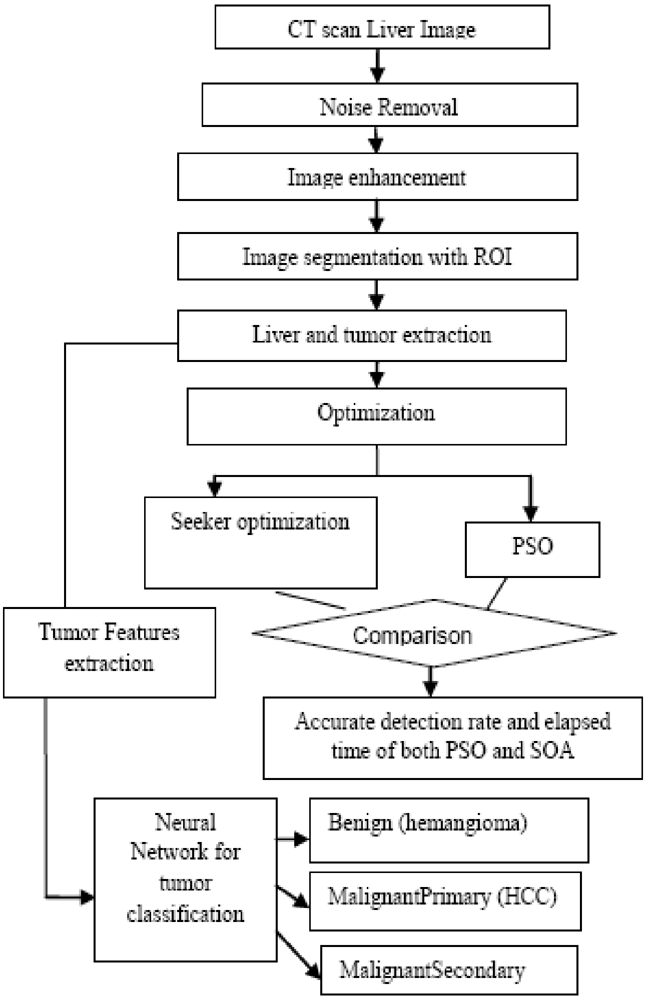

Figure 1: Flowchart

III. SEGMENTATION

Segmentation is a technique that subdivides a digital image into multiple segments. Segmentation is based on one of two basic properties of intensity: similarity and discontinuity [4]. Detecting Similarities means to partition an image into regions that are similar according to a set of predefined criterion this includes image segmentation algorithms like thresholding, region growing, region splitting and merging. Detecting Discontinuities means to partition an image based on abrupt changes in intensity, this includes image segmentation algorithms like edge detection.

Different Approaches for Medical Image Segmentation:

- Level set
- Edge Detection
- Threshold Based
- Clustering Based
- Region Based

Liver tumor segmentation is done with region based approach in this thesis work. Region based methods partition an image into regions that are similar according to a set of predefined criteria where as other segmentation approaches like edge detection methods partition an image according to rapid changes in intensity near the edges. Region based segmentation approach provides good results on contrast enhanced images and is immune to noise. Region growing methods can correctly separate the regions that have the same properties.

A. Region based approach

Region-based segmentation schemes attempt to group pixels with similar characteristics into regions. Conventionally, these are global hypothesis testing techniques. The process can start at the pixel level or at an intermediate level. Generation and filtering of good seed regions of high confidence is essential. There are two approaches in region-based methods: region growing and region splitting. In the region growing methods, the evaluated sets are very small at the start of the segmentation process. The iterative process of region growing must then be applied in order to recover.

Region growing is procedures that make groups of pixels in whole image into sub regions or larger regions based on predefined criterion. Region growing can be processed in four steps:-

i. Select a group of seed pixels in original image.

ii. Select a set of similarity criterion such as grey level intensity or color and set up a stopping rule.

iii. Grow regions by appending to each seed those neighboring pixels that have predefined properties similar to seed pixels.

iv. Stop region growing when no more pixels met the criterion for inclusion in that region [5].

Compared to edge detection method, segmentation algorithms based on region are relatively simple and more immune to noise. Edge based methods partition an image based on rapid changes in intensity near edges whereas region based methods, partition an image into regions that are similar according to a set of predefined criteria.

B. Optimization

Optimization is the search for a set of variables that either maximize or minimize a scalar cost function, $f(x)$. The n-dimensional decision vector, x consists of the n decision variables over which the decision maker has control. The cost function is multivariate since it depends on more than one decision variable, as is common of real-world relationships. The decision maker desires a more efficient method than trial and error by which to obtain a quality decision vector, which is why optimization techniques are employed. In general, the literature focuses on minimization since the maximum of any cost function, $f(x)$, is mathematically equivalent to the minimum of its additive inverse, $-f(x)$. In other words, any scalar function to be optimized may be treated wholly as a minimization problem due to the symmetric relationship between the cost function and its additive inverse across hyperplane $f(x)=0$.

Optimization algorithms used in this work are **:** Particle Swarm Optimization (PSO) and Seeker Optimization Algorithm (SOA).

a). Particle swarm optimization (PSO)

Russel Ebenhart (Electrical Engineer) and James Kennedy (Social Psychologist) in 1995 (both U. Indiana, Purdue) inspired by the social behavior of birds, studied by Craig Reynolds (a biologist) in late 80s and early 90s. He derived a formula for representation of the flocking behavior of birds. This was later used in computer simulations of virtual birds, known as Boids. Ebenhart and Kennedy recognized the suitability of this technique for optimization. PSO is a robust stochastic optimization technique based on the movement and intelligence of swarms. PSO applies the concept of social interaction to problem solving [6,7,8]. In PSO, Initialize particles with random position and velocity vectors. For each particle position evaluate fitness. If new position is best than set it for whole population. Identify than global best. Update the particle and velocity equations 3.1 and 3.2. Figure 2 gives the algorithm of PSO below:

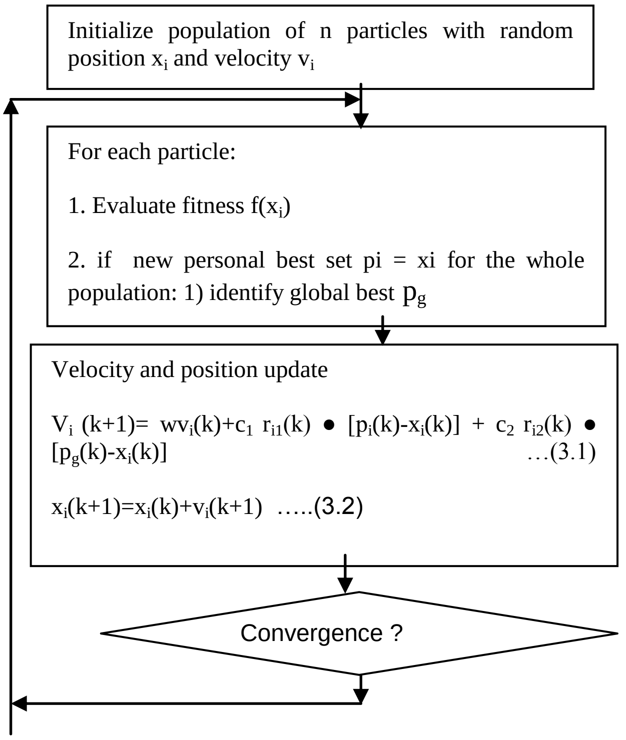

Figure 2: Flow chart of PSO optimization
(Source:www.georgeevers.org/particle_swarm_algorithm)

b). Seeker Optimization

The SOA is based on the concept of simulating the act of humans' intelligent search with their memory, experience and uncertainty reasoning. In this sense, the individual of this population is called seeker. SOA has shown better global search ability and faster convergence speed for most of the chosen benchmark problems, especially for unimodal benchmarks. Seeker *I* has the following attributes: the current position $x_i = (x_{i1}, x_{i2, \ldots\ldots\ldots,} x_{iD})$, the dimension of the problem D, the iteration number t, the personal best position $p_{i,\ best}$ so far, and the neighborhood best position g_{best} so far. The algorithm uses search direction and step length to update the positions of seekers [10]. In the SOA, the search direction is determined by seeker's egoistic behavior, altruistic behavior and pro-activeness behavior, while step length is given by uncertainty reasoning behavior. Search direction α_{ij} and step length d_{ij} are separately computed for each individual i on each dimension j at each iteration t, where $\alpha_{ij} \geq 0$ and $d_{ij} \in \{-1;0;1\}$.

At each iteration the position of each seeker is updated by:

$x_{ij}(t+1) = x_{ij}(t) + \alpha_{ij}(t) \bullet d_{ij}$ (3.3)

where i = 1,2,….., SN; j = 1,2,…., D (SN is the number of seekers). Also, at each iteration, the current positions of the worst two individuals of each subpopulation are exchanged with the best ones in each of the other two subpopulations, which is called inter-subpopulation learning. The pseudo-code for the SOA is:

t= 0;
Generate SN positions uniformly and randomly in the search space;
Evaluate all the seekers and save the historical best position;
repeat
Compute search direction and step length for each seeker;
Update each seeker's position using equation (3.3) evaluate all the seekers and save the historical best position;
Implement the inter-subpopulation learning operation;
t=t+ 1;
until $t=T_{max}$

PSO which is computationally very efficient optimization technique is proposed for brain tumor image segmentation. The proposed method is relatively simple, reliable, and efficient. The efficiency was compared with GA. PSO provides better performance comparing with GA. PSO with FCM algorithm has been used to find out the optimum value. It can be concluded that the proposed approach has lower tumor value and lesser execution time. There is a decrease beyond 80% in both the values when compared to any other existing approach [11].

IV. RESULTS

Results of all 15 cases of different patients having liver tumors, used for testing in this research work.Testing Results of all cases are true or false as compared with the results of the database created.

Table 1 gives the comparison of two optimization techniques used in this thesis for classification of tumor. The comparison is made on the basis of testing accuracy and elapsed time.

❖ **Accuracy**: Accuracy is used as a statistical measure of how well a binary classification test correctly identifies or excludes a condition**.**

Mathematically:
Accuracy =
No. of TP + No. of TN ⁄ No. of TP + FP + TN

True Positive (TP) : Sick people correctly diagnosed as sick.

False Positive (FP) : Healthy people incorrectly identified as sick.

True Negative (TN): Healthy people correctly identified as healthy.

False Negative (FN): Sick people incorrectly identified as healthy.

❖ **Elapsed time**: The amount of time that has passed since a particular process started especially compared with the amount of time that was calculated for it in a plan.

SOA TP = 1 case ; SOA TN = 8 cases;
SOA FP = 6 cases
PSO TP = 6 cases ; PSO TN = 8 cases;
PSO FP = 1 case

PSO testing and classification accuracy =
(No. of TP + No. of TN)⁄ (No. of TP + FP + TN)
= (8+6)/ (8+6+1) = 93.33%

SOA testing and classification accuracy =
(No. of TP + No. of TN)⁄(No. of TP + FP + TN)
=(8+1) /(8+6+1)
= 60%

Table1 shows the comparative results of SOA and PSO on the basis of testing and classification accuracy and elapsed time.

Table 1: Comparison of PSO and SOA testing accuracy and elapsed time

	TP	FP	TN	Testing Accuracy percentage	Elapsed time
SOA	**1**	**6**	**8**	**60%**	**48.744537**
PSO	**6**	**1**	**8**	**93.33%**	**42.429959**

V. CONCLUSION

In this thesis, region based segmentation process is used for segmentation of liver and tumor from CT scan image of abdomen. PSO and SOA optimization technique results are compared for optimized detection of liver tumor. PSO resulted in 93.3% detection and classification accuracy while SOA gave 60% detection and classification accuracy. In term of elapsed time for training process SOA took 48.744537 seconds and PSO took 42.429959 seconds.PSO gives better result in terms of detection and classification accuracy and elapsed time for training process in comparison to SOA.

Particle Swarm Optimization has been used previously in diagnosis of brain tumor and gives 92.3% results with MRI images of brain. SOA has been used extensively in mathematical analysis of problems. So, SOA and PSO algorithms have been used in this thesis work to train the neuron and with these trained neurons classification of liver tumor is possible.

Here, only 30 cases were used to train the neurons and 15 cases were used to check the detection and classification accuracy with the code generated for training the neurons. In some cases PSO gives accurate result as compared to the database reports and in some cases SOA is accurate. Still there is some scope of improvement in this work. In the future, this work can be extended to get improved results by utilizing approaches that involve the fusion of one or more optimization techniques.

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