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Medical Image Processing Schemes for different Cancer Detection system

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Abstract— *In this paper, the survey has been proposed on―Medical Image processing schemes forcancerdetection‖.The various intelligent schemes available in the literature for cancer detections have been discussed. This paper provides details of different techniques that reveal how hybrid intelligent approaches are applied to different categories of cancer detections and treatments. The three major categories of cancer problems such as breast, liver and brain tumor using cancer data bases are clearly discussed. The methods and algorithms used for detecting cancers are FPGA(Field Programmable Gate Array) based 3-D Ultrasound Computer Tomography(3D-USCT) with image reconstruction algorithms, a resistively loaded wire bowtie antenna using genetic algorithm approach,* $^{(111)}$ *In –pentetreotide Single-photon emission computed tomography(SPECT) based on Monte Carlo simulation and CA (Cellular Automata) Based Segmentation method. By reviewing all the methods available in the literature, it is found that each method has its own merits and demerits. This paper illustrates overview of various states of methods available in the cancer detection and comparison analysis of each method isdiscussed.*
Keywords:*FPGA,3-D USCT, reconstruction algorithms,* $^{(111)}$ *In –pentetreotide SPECT, Monte Carlo simulation, CA algorithm.*

I. Introduction

The impact of digital images on modern society is tremendous, and image processing is now an important component in science and technology. Medical imaging is often perceived to designate the set of techniques that noninvasively produce images of the internal aspect of the body. In this restricted sense, medical imaging is seen as the solution of mathematical inverse problems.

In this survey the three different types of cancers such as liver, brain and breast cancers are analyzed with different methods and algorithms. In Fig.1 the image modality used for the detection of liver cancer is SPECT and the method used to reduce the noise and identify the cancer is collimator based Monte Carlo simulation. In brain cancer identification the Magnetic Resonance image (MRI) is acquired and the method used for segmentation is CA segmentation. The breast cancer is detected with the help of two methods one is 3-D USCT method and another one is bowtie antenna based signal analysis method.

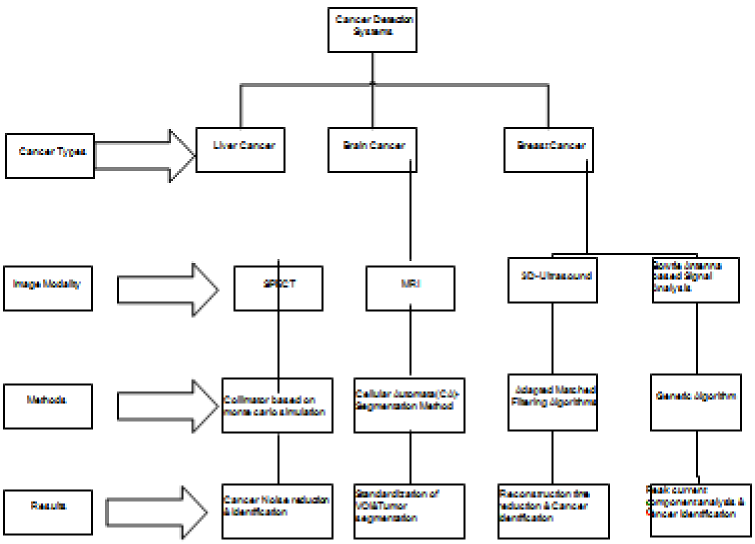

Fig.1 Overview of Cancer detection Schemes

II. Methods Andmaterials

A. Breast cancer detection systems using BowtieAntenna

The early breast cancer detection is done by clinical screening programmes. The microwave sub-surface radar used in medical imaging will provide several advantages. This technique detects dielectric contrast between the normal cell and the cancer cell efficiency, accurately and securely [1]. This will be achieved by establishing the antenna and RF (Radio Frequency) subsystems with low cost and using compact ultra wide band antenna elements for better communication but such antennas are not adapted for microwave imaging system. They are in need to transmit and receive a short transient pulse with minimum distortion and low level of late time imaging[3].

To achieve this Chan Hwang see, 2012 proposed bowtie antenna technique for imaging system because it produce non-dispersive ultra wide band operating frequency with low cost. The discussion of input admittance and the radiation is done by the brown and Woodward method. The bow antenna is lying between the cylindrical monopoles and the conical monopoles with respect to the broadband performance[1].

The transient pulse is easily transmitted and received by the bowtie antenna. To radiate, the pulse antenna will have a minimum late-ringing time. It is done by resistive load to the radiator section by this way the internal reflections are reduced. Bowtie structure is in the form of series of wires andtheirperformanceisselectedfromthe–genetic optimization‖ however this structure is used for limited measurements.

The antenna design [2]-[4] is based on wire bowtie structure. In this system the antenna size is changed into the minute size and the geometry parameters are optimized with respect to the load resistors and the simulated values are defined with measured values.

The main objective is to achieve the suitable antenna geometry with strong input impedance thus the late-time ringing is reduced by internal reflections. The CST (Computer Simulation Technology) microwave studio is used for final design analysis [4]. For optimization EM (Electro Magnetic) simulation algorithm is used to compute the antenna performance. The genetic optimization starts with Initialization of variables and constants the target parameters are assigned to the cost function. The total antenna dimension is 70.3 x 37mm^3. In this 3 wires and 6 resistors are used.

The simulated VSWR (Voltage Standing Wave Ratio) performance of unmodified antenna and resistivity loaded structure is compared in free space. In this, the impedance bandwidth is approximately 26.42% for VSWR is <2. It is enough for target interval of 4 GHz to 8 GHz. To improve the bandwidth, the resistive loads are added and dielectric losses appear to reach high impedance above 8.5 GHz [1]. The prototype antenna is Arlon‘s ―foam clad‖ material.Its permittivity varies from 1.15 to 1.30. One half of the antenna takes the place of 50 x 50 cm^2 ground place as monopole [4]. To construct the practical tissue model the immersion liquid and fatty tissues where analyzed. It has the same electrical properties as vegetable oil. The rectangular cross sectional tank of 54 x 30 x 11cm^3 is filled with vegetable oil. Unwanted reflections are eliminated through RF absorbent sheets. The insertion loss was better than 1 dB. In this ‗S‘ parameter measurements are used for input power and near field radiation pattern is measured by E- field probe (model Ex3 DV4)[1].

For the measurement of radiation efficiency, the distance between the antenna and the probe is kept 8 cm. For the simulation, the candidate antenna structure is 15 x 15 x 15cm^3. It is in the shape of spherical ball with a radius of 5 mm. To verify the simulated result, 1.0 x 1.0 cm^2 metal plates is placed at the distance of 3 cm. where the scattering centre is located at 1.5 cm and 3 cm respectively. Finally, the measured and simulated results arecorrelated.

Thus, the design of bowtie antenna in medical imaging system for cancer detection using ―genetic algorithm‖ is analyzed. In this paper the author designed the candidate structure with experimental setup and the prototype antenna is designed for scattering detection [1].

B. Breast Cancer Detection using FPGA Based 3-D Ultrasound ComputerTomography

The normal screening methods sometimes failed to diagnose the cancer in the initial stage, the sensitive method will enable to diagnosis the cancer in earlier state and thus increase the survival probability of the patient. To improve this situation three-dimensional ultrasound computer tomography (3D-USCT) promises a high-quality volume images of the breast. The investigation of FPGA based processing for a set of signal processing algorithm is proposed by Matthias birk, 2011. In the approach the processing time per data set is approximately 50µs, which takes less than 30% of device resources [13]-[14].

3D-ultrasound computer tomography consists of 628 ultrasound emitters and 1413 receivers. The ultrasound wave from the emitter is allowed to fall on the female breast to detect the cancer. During measurements, the breast is surrounded by many ultrasound transducers. The ultrasound wave hits the breast cell and reflects back. This reflected ultrasound wave front is recorded by all surrounding receivers. The recorded signal is pressure variation overtime called A-scan[13]-[15].

In 3D-USCT, the ultrasound waves are made to fall at many different angles. This 3D rotation of the ultrasound transducer results in producing 3.5 million A-scans. This 20 GB of raw data is recorded for each breast and it is acquired using FPGA based Data Acquisition system (DAQ). This is further transferred to PC for image reconstruction which is a time consuming process. The proposed approach helped to reduce the reconstruction time. It deals with the FPGA based processing for a set of signal processing algorithm. It mainly deals with a focus on increasing the processing performance and reducing the resource utilization. This FPGA based DAQ occupies only 17% of the available logic elements. 97% of the embedded multipliers and less than 1% of the memory bits on each computation FPGA. Thus, the FPGA implementations reduce the processing time by the factor of 6.9 for the time domain based approach. [21]- [23]

In 3D-USCT [23]-[24], Adaptive Matched Filtering algorithm (AMF) is used as a signal processing algorithm which is ported to the FPGA in the DAQ. The AMF preprocessing technique increases the Signal to Noise Ratio (SNR), resulting in an improved overall image contrast. This AMF algorithm is applied separately for each A-scan obtained from the ultrasound emitter. The A-scan is used by the Synthetic Aperture Focusing Technique (SAFT) to reconstruct a 3D-volume image of the breast.

C. Frequency domain approach

In the first pass, A-scan is transformed, multiplied with the conjugate complex of the matched filter and transformed back to the time domain. In second pass, the peak detected signal is transformed to frequency domain, multiplied with the optimum pulse and subsequently transformed back to the timedomain.

The frequency domain based processing takes 120 µs. The resource utilization of the computation FPGA in frequency domain is Logic elements (71%), Multipliers (9 bits) (47%), Total memory bits (83%) and the speed up factor for processing per A-scan is2.9.

D. Time domain approach

This method is adopted by converting the correlation, convolution with the matched filter and the result is convoluted with the optimum pulse into a finite impulse response (FIR) filter. As it is a time domain approach, it is not necessary to split the A-scan image into six sequential parts. The time domain based processing takes 50.5 µs for processing each A-scan [9]. Thus the proposed FGPA implementation reduces the processing time by a factor of

6.9. The resource utilization of the computation FPGA in time domain are Logic elements (27%),Multipliers (9 bits) (0%) and total memory bits (<1%).

Thus the processing time per A-scan on a single computation of FPGA, clocked at 60 MHz is over 2.3 times faster than the frequency domain processing. The technique is installed in the computation FPGA and in the DAQ system with the processing of the A-scan. Thus the preprocessing time is reduced. The AMF and a set of signal processing algorithm applied as preprocessing steps in 3D- USCT.The only drawback of time domain processing is that the filter co-efficients are hard coded into the FGPA fabric and are not changeable at runtime[13].

III. Liver Tumor Detection Based Onmonte Carlosimulation

Visually detecting the small tumors is the good successful treatment of the cancer disease. The SPECT has high ratio of tumor-to-background-uptake. For the detection of small liver tumor in liver background Emma Mahler, 2012 proposed and compared three different parallel-hole collimators regarding contrast as a function of image noise for a phantom simulation, liver, which is a common region for somatostatin-positive metastases. The three types of collimators are Low Energy General Purpose (LEGP), Extended Energy General Purpose (ELEGP) and Medium Energy General Purpose (MLEGP)[5]-[7].

ELEGP collimator proved to be the most optimal for the smallest tumors both with and without model based compensation. All raw-data projections are produced using Monte Carlo simulations [5]-[6]. With Ordered Subset Expectation-Maximization (OSEM), reconstructions were performed both with and without model-based compensation. Somatostatin receptor scintigraphy (SRS) using $^{(111)}$in-pentetreotide_(Octreoscan), Tyco healthcare, Mallchrodl well established method has high accuracy for visualization of neuroendocrine tumors (NETs). $^{(111)}$In penteheotide is the most commonly used somatostatin analog and SPECT gives information for better staging and tumor followup.

In day 1, the patient is injected with about 160 MBq in- pentetreotide. In day 2, SPECT examination is performed. This is examined by using an Infinia Hawkeye SPECT system.

It is taken by two Field Of View (FOV) one over the chest and one over the abdominal region. These two will be merged, in the reconstruction resulting one reconstructed image volume. Taking two FOV will reduce the missing unexpected tumors on the region. But the artifacts limits the acquisition time per FOV.

A MEGP collimator is used because of following reasons. It has a higher energy emission of 245 KV and relatively low sensitivity it combined with the short acquisition time per FOV. The resulting image has relatively high noise level. This method is used for detecting small tumors having high activity background such as liver but one disadvantage is that it suffers from high noiselevels.

The comparison of three collimators [9] and its evaluation is performed using tumor contrast as a function of background noise since the collimator showing the highest contrast for a certain background noise level is the most optimal for detecting the tumors for a more direct comparison of contrast and noise.CNR (contrast to noise ratio) is also give some guidance to the optimal number of iterations.

A digital cylindrical phantom consisting of tumor-like spheres is a homogeneous background corresponding to uptake of the radiopharmaceutical in liver. The two spheres are located in opposite ends of the cylinder and the setup plane is described to make the phantom correspond to a realistic in SPECT study, 20 anonymized patient images from the Nuclear Medicine Department at the University Hospital of Umea is selected, 10 patients had been diagnosed with somatostatin-positive metastases in liver and 10 were without visible liver disease[9].

The average tumor-to-background ratio is calculated to 11.3 (±3.0) for the 15 tumors and the sphere-to-background ratio in the phantom are set to this value. The corrected average number of counts per pixel for all 10 patients is calculated to 13.8 (±4.5) [9].

A. Reconstruction

Reconstruction (Compton window) of MEGP, ELEGP,For the corresponding MEGP reconstruction[13] without scatter correction, an effective _broadbeam' attenuation coefficient 0.092 cm^{-1} is used for simulation. For the LEGP reconstructions, attenuation correction is discarded due to the already heavily overcompensated region in the center of the reconstructionimages.

This paper more interested in tumor detection and the intensity difference between tumor and background. In the model based compensation the high sensitivity is positive for lesion detectability, contrast is high and quantitative accuracy, model-based compensation is a clear advantage for small tumor detection, ELEGP collimator is the optimal method to detect the small spheres in liver both with and without reconstruction. In the LEGP collimator the contrast is high but the convergence is slow so it is not recommendedforsmalltumordetection.IntheMEGP collimator the scatter correction results in the highest contrasts at the expense of noise [5].

IV. Brain Tumor Detection Using Cabased Segmentationmethod

A CA based seeded tumor segmentation method is proposed by Andac Hamamci, 2012 for the analysis of brain tumor. This method is done on contrast-enhanced T1 weighted MR images. This MR image is standardizing the Volume Of Interest (VOI) and seed selection [8]-[12]. For the response to the therapy and researchers in radio surgery planning, this method presents a fast and robust practical tool for segmentation of solid tumor with minimal user interaction.

The shortest path problem is solved by the iterative CA framework. For this the connection of CA based segmentation to the graph theoretic methods is established. After that the state transition function of the CA to calculate the shortest path solution is modified [11].

To adapt the segmentation problem, a sensitivity parameter is introduced. A line drawn on the maximum diameter of the tumor are gathered to initialize the algorithm and an algorithm based on CA is presented to differentiate necrotic and enhancing tumor tissue content are very important for a detailed assessment of radiation therapy. The data sets demonstrate 80% - 90% overlap performance of the algorithm [8]. First outlining the brain tumor is done by MRI. MR images are getting by the administration of a contrast agent (gadolinium), blood vessels and parts of the tumor where the gadolinium is pass the blood brain barrier are observed as hyperintensearea.

Population atlases provide an important prior to improve segmentation by measuring the differences between the normal brain and tumor brain. The main problem is deformable registration of brain images with tumor. The different performance measures are Dice overlap, jaccard Index, False Positive and Negative Volume Fractions (FPVF, FNVF).Overlap is common measure, the Table.1 shows the percentage of overlap stated by different authors [8].

Table 1. Percentage of average overlap

S.No	Name of the authors	Average overlap
1	Prastawa et al	86.7% average overlap (1.5h processing time)only 3 patients
2	Menze et al	60% average overlap on 25 glioma patients
3	Gooya et al	74.5% average overlap on 15 glioma patients (processing time 6-14h)
4	Liu et al	95.6% average overlap5 patients over 10 patients

In contrast-enhanced T1-weighted MR images the minimal use interaction, efficient and robust segmentation of brain tumors is focused. The gradient-based techniques for segmentation have the advantages of greater robustness to noise ratio. Graph based seeded segmentation framework has been generalized such that Graph Cuts (GC), Random Walker (RW), shortest path and power watersheds are done by general seeded segmentation algorithm. This algorithm solves a minimization problem. This method re-examines the CA algorithm and CA framework solves the shortest path problem. The framework for the complete segmentation in brain tumors and the necrotic regions is defined in detailed [8].

A. Tumor-Cut Algorithm-CA based tumor segmentation algorithm The user draws a line in visible diameter of the tumor then VOI [20] is selected with F (red) and B (blue) seeds and then tumor algorithm is run and obtaining F and B at each vonel mapping of combined to obtain the tumor probability a set level set surface is initialized at PT equalto 0.5 finally necrotic regions of the tumor is segmented using CA.

B. Seed selection Based on Tumor ResponseMeasurement Criteria

This procedure is used to evaluate the treatment response of the solid tumors. It focuses on segmentation problem. The result of labeling is done by the data inside the region. Computation time is significantly reduced. After VOI, the line is cropped by 15% from each end and thickened to 3 pixels wide after this selection, the bounding box of the sphere has a diameter 35% longer than the line and one- voxel wide border of this VOI is used as background. In the data set, 100% coverage is achieved with 2 times enlargement and which covers 99% of all tumors[8]-[11].

C. Level set Evolution on Constricted TumorProbability MAP

Smoothing is done with the three reasons they are,

i) For Considering the area surrounded by the tumor tissue as a tumor region even the intensity characteristics are healthy.
ii) To add misclassified necrotic regions to tumorregion
iii) To eliminate nearby vascular structures that are improved by administration of the contrastagent

The CA algorithm has advantages that the measuring of distance of each cell is possible and each class seeds are run separately with the help of CA. Depending on the result obtained from the graph-theoretic approach the proper intelligent smoothing of the tumor borders will be included with the interactive tumor segmentation [8].

D. Enhancing/Necroticsegmentation

The quantification of the necrotic regions which present in the tumor is the major problem during the tumor progress. Delayed radiation necrosis is the primary risk associated with the stereotactic radiosurgery. Necrotic classes are produced due to the different intensity characteristics using multiprotocol intensity classifiers. The necrotic and the parts of the tumor are enhanced using CE-T1 weighted MRIvolumes.

In CE-T1 MR images, the necrotic parts are observed as the hyper intense to indicate there is no blood flow into these regions without any prior information the segmentation is applied by necrotic label using intensity threshold. To choose this threshold, expectation maximization and Otsu‘s method are used. Instead of simple thresholding, the CA algorithm is chosen for two thresholds [8]-[12].

E. Data and EvolutionMethods

i) Synthetic data sets of simulated tumor from Utah: In this, five synthetic brain tumor data sets are taken. The utilized data is simulated the contrast enhanced T1- weighted MRI images with tumors and the ground truth segmentation isprovided.
ii) Harvard Brain Tumor respiratory: Performance of different algorithm iscompared.
iii) Brain Tumor data sets are taken from Clinical Radiation Oncologysite.

The tumor contours outlined manually by a radio-oncologist for radio surgery planning. Dice overlap is usedto quantify the overlap between obtained segmentationmaps and the _true‘ segmentation. Segmentation methodmeasures the robustness. The performance measures, Diceoverlap, mean, median and maximum surface distancesand volume percent errors between the ground truthsegmentation and result of the algorithm are reported. TheDice overlap is on the average 83%, the segmentation isimproved by smoothing out the tumor borders, andavoiding sharp protrusions. Sensitivity, specificity andtotal correct fraction values evaluated by STAPLE [8]-[9].The Strengths of this method include its simpleinteraction over a single slice and less sensitivity to theinitialization, its efficiency in terms of computation timeand robustness with respect to different and heterogeneoustumor types. The user interaction time is just a fewseconds and typical computation times vary between 1s/ to 16 min.

V. Results And Discussions

The various techniques and algorithms used for detecting brain, liver, and breast cancers are analyzed and compared with the different types of measured parameters. The table.2 illustrates the comparison of cancers

Types of Cancer	Methods used	Measured Parameters and Values	Remarks
Breast cancer	1.A restively loaded bowtie antenna with genetic algorithm approach	Peak current component for simulated output with the scattering center - 0.8ηs(1.5cm) Peak current component for measured output with the scattering center- 1.1ηs(3.0cm)	Prototype antenna has sufficient sensitivity for its future application
	2.FPGA(Field programmable Gate array) -3- D Ultrasound computer tomography with adapted matched filtering algorithms	Frequency domain Time-120µs Speed up factor-2.9 Logic Elements-71% Embedded multipliers(9bits)- 47% Total memory bits- 83% Time Domain Time-50.5 µs Speed upfactor-6.9 Logic Elements-27% Embedded multipliers(9bits)- 0% Total memory bits- <1%	Time domain approach is the best method
Liver cancer	$^{(111)}$In pentetreotide SPECT-A Collimator basedon Monte Carlo simulation	Contrast to noise Ratio is Measured for Different Types of Collimators MEGP-3 Iterations ELEGP-4 Iterations LEGP-15 Iterations	ELEGP is the most optimal for the detection of small spheres in liverback ground
Brain Tumor	Cellular automata(CA)b ased segmentation method – MR(Magnetic Resonance) Images	Overlap range-80%- 90%	Computati on time is reduced due to inherent parallelity of the proposed algorithm

Table.2 Comparison of Cancers

VI. Conclusions

In this paper, a survey has been made on the different types of methods and algorithms used for cancer detection. The three different hybrid intelligent methods obtained in the literature for cancer detections are reviewed in detail. The three major cancer problems such as breast, liver and brain tumor using cancer data bases are analyzed and among that CA based segmentation method is comparably efficient method since the computation time is low due toinherent parallelity of the proposed algorithm. The future work is to develop hybrid intelligent algorithms for image analysis and to examine the real time cancer images and provide better solution for analysis and diagnosis.

The data set consisting of 150 real time images in the format of DICOM are collected from Clarity Imaging centre for different categories, age and ethnic groups, and the new algorithms will be clinically validated for its effectiveness with the help of radiologists and physicians.

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