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Envisage The Lung Tumor Evolution In PET-CT Images During Radiotherapy

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Abstract:

The proposed technique is capable of estimating lung tumor growth and its effectiveness by applying patient specific model on tumor growth model. That is desirable to predict the lung tumor growth rate so that appropriate treatment can be planned in early stage. The work presents the methodology that consists of three steps: advection, Proliferation, Treatment. The partial differential equation is base of formulating these terms. Using optimization the estimating parameters are modeled from sequence of observed images. Evaluating tumor by enacts 3D optical flow through sequential images. The proposed ADR equation with LBP intensity features are employed to simulate the tumor growth model and define the predicted tumor contours, tumor volumes. The result will indicate a very good ability of the proposed method for estimating model parameters of lung tumor volume and its variations. It shows a satisfying agreement between predicted tumor contours.

Keywords: **ADR equation, Patient-specific model, Tumor growth prediction, Local binary pattern algorithm.**

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INTRODUCTION:

Statistics shows lung disease death rate is still on the rise. The high mortality rates of lung disease have encouraged many researchers to focus their efforts on improving their diagnosis and treatment methods. In lung tumor diagnosis, wide range imaging protocols are routinely used to evaluate ameliorative options or to monitor the state of the disease. The detection of changes in metabolic organs during treatment, the (FDG) positron emission tomography (PET) has strongly abstract the clinical management of patients with lung cancer. Little progress has been made toward the construction of modeling tumor growth parameters. It describes the growth of lung tumor and its volume variations. First it provides a better understanding of the tumor physiology growth. Second, it helps to predict the tumor evolution from limited number of sequential images. Third, invoke mathematical model could be used to quantify the aggressiveness of tumor in a patient. Last, such a model could improve therapy planning in radiotherapy by defining better invasion margins basis on the local estimation parameters of the tumor cell density. PET-CT images would be very useful in tumor modeling procedures usually performed during radiotherapy. For modeling tumor growth the ODE equations are applied and proved to be great interest of realistic applications. The disadvantage is to estimating parameters of tumor volume. There has been large amount of research on mathematical descriptions of tumor growth dynamics both at microscopic and macroscopic scales. At microscopic scale invoke a mathematical model for knowing about invasion of intracellular dynamics of tumor. In macroscopic it shows the large scale dynamics such as average behaviour of tumor, its spatial evolution, and its mass effect on lung have been addressed. Mathematical tumor growth modeling based on partial differential equations tries to explain the complex dynamics of tumor progression as a function of biological process that are known or assumed from prior experiments. The ADRE-based models dedicated to modeling diffusive tumor at microscopic level. Such processes shows the dynamics of individual tumor cells, its interactions with each other and could explain the tumor cells interact with surrounding tissues biological and allocation of substances to relevant biochemical process. The ADR equation with LBP intensity based features is employed to simulate the tumor growth model and define the predicted tumor volume and SUV.

Olivier Clatz estimates a new technique to simulate the growth of Glioblastoma multiforma (GBMs), while it is most aggeressive glial tumor at three-dimensional (3D). The effect is modeled Gompertz equation with reaction diffusion and latter based on a linear elastic brain constitutive equation. Proposing new coupling equation taking into account the mechanical influence of tumor invaded structure. [5]. ***Ender Konuko*****glu** proposes a parameter estimation method from series of images at time series to enactment of reaction-diffusion tumor growth model. Showing several parameters can be identified uniquely in the case of fixing one parameter. In this the tumor delineations are extracted from MR images. In this the tumor boundaries are extracted by manually or automatically using segmentation algorithm. [6]**.** ***Ali Gooya*** presents an approach of expectation maximization (EM) algorithm that provides a glioma growth model. The set of optimal parameters are estimated for the tumor model by segmentation and atlas registration. Optimal parameters are estimated through low dimensional descriptions of the patient scans. The method shows an automated segmentation done in scanning images and results are compared to drawn tumor model. [10]. ***Xinjian Chen*** proposed 3-D tumor growth prediction system using longitudinal images by finite-element-method (FEM).The method estimate the simulation of coupled tumor growth model. Objective function optimized by overlap accuracy using a hybrid optimization parallel search package estimate parameters for tumor model. After optimization of parameters are applied to tumor growth model and getting prediction results at time instances of n+1. [11].***Thierry Colin*** suggested the technique for tumor growth model based on parametric system of partial differential equation. The mathematical models used for clinical applications that are based on sets of Ordinary Differential equation (ODEs). For spatial aspect of tumor growth modeling approach based on the partial differential equation (PDEs). The 2D Darcy type applied for tumor growth modeling and it account main physical features of tumor growth. The method has a high performance database and computation with auto-correlation matrices. [9]. ***Marianne Morris*** propose classification-based diffusion model (CDM) that shows a prediction of glioma will grow at a voxel's-level based on the features of specific patient tumor properties and attributes of voxel's in MRI images. The method compared with two other approaches of Naive uniform growth model and Tissue-based diffusion model. The method reduces the iterations in tumor growth modeling and improves the accuracy. [13]. ***CSAIL*** designed a method to determine the tumor growth model by using reaction- diffusion formalism. The Fisher-Kolmogorov model simplifies the tumor growth evolution and gives large number of multi model, multi temporal images.

The method is proposed to estimate the macroscopic models for tumor growth based on medical images. Using partial differential equation which can describe more complex biological phenomenon's involved in tumor growth through modeling. The combination of advection-diffusion equation can estimate parameters of tumor in lungs from PET-CT image sequences with known volumes. At last the results indicate a very good ability of the proposed technique for estimating the lung tumor modeling in an image sequences.

I. Proposed Method

A. Initialization

Image classification is defined as the process of assign corresponding levels with respect to groups with homogeneous characteristic, with the aim of discriminating multiple objects from each other within the image. In classification maximum likelihood estimated to maximize the probability from a defined probability density function within the feature space. The proposed modeling method estimate a parameters based on novel image sequences classification technique that determine the optimization systematically. The concept behind this technique takes advantage of the fact that the tumor velocity and volume considered by a 3D-optical flow with local binary intensity features through lung tumor contour, size and shape from image sequences. An optimization problem consists of maximizing or minimizing real function by systematically choosing input values from within an allowed set and computing the value of the function. The best available values of some objective function under on domain include different types of objective function and different domain through Optimization. The proposed lung tumor volume estimation method based on ADR equation with intensity based features and formulated into three terms.

B.Architecture Design

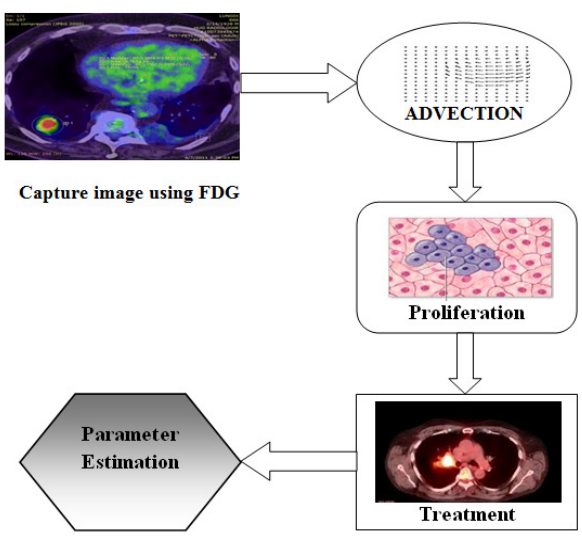

Fig 1: Overview Design

The advection causes distribution of oxygen, nutrients and space. The tumor cells moves to larger space with higher concentration of oxygen or nutrients. This is mathematically describes as advection. Also estimates tumor velocity v by 3D-optical flow with Darcy-Type law through PET-CT acquisitions. In proliferation using Gompertz growth law model the dynamics of tumor growth and fix the proliferation range. That has been shown an increased number of tumor cells. During radiotherapy the effect of tumor cells can be known from treatment which estimates cell survival probability after exposition of radiation.

C. Algorithm

The proposed method using distribution based classification approach which comparing obtained optimization values with well known circular-symmetric auto regressive random (CSAR) modeling. Several rotation angles are used in this approach which results good estimation parameters for modeling. The local binary pattern feature for texture classification determined and combined with histogram oriented gradients.

$$LBP_n = S\,(g_i - g_0)2^{i-1} \quad ....(1)$$

Similarly, producing rotation invariant local binary pattern could be extracting the features of tumor contours, size and shape for modeling.

$$LBP_n^{ri36} = \min\{ROR(LBP_8,i) \mid (i = 0,1,2....n)\} \quad ......(2)$$

This framework attempts to estimate the parameters of small tumor contours shape and size because it would be enlarging the pixels of image sequences for modeling which results accuracy of predicting tumor growth. The texture classification done by estimating the parameters of α, β, ζ from image sequences at time instant at t_i-1. Thus the volume of tumor can be calculated by

$$Y(s) = \alpha * \ln(\beta) + \zeta \quad .... (3)$$

Thresholding is a simple technique, which divides the images into specific classes by comparing each image pixel value with number of intensity value called thresholds. The most important step in the thresholding method is fine tuning the threshold values because those values have important influence on the accuracy of image classification. The proposed method using several rotating angles for classifies the image. The classification test sample was S was assigned to the class of model M that maximized the log-likelihood measure:

$$L(S, M) = S_b (\log M_b) \quad ......(4)$$

In modeling, it using multidimensional optimization to estimate parameters with good accuracy, signal to-noise-ratio, good spatial resolution as well as associated partial volume effects. Volume-does model has been derived for knowing tumor volume V that decrease exponentially after radiation dose D accumulatively and observed volumes are 73.89 and 24.03 respectively. To obtain a performant tumor evolution prediction, α'_{eff} governs the speed of volume decrease and it can be estimated by fitting the expert-based measurements.

II. Result Analysis

The analysis includes an optical flow through image. Optical flow is an approximation of the local image motion based upon local derivatives in a given sequence of images. It indicates the intensity and the direction of each voxel's movement between two images. To acquire the tumor contours on the predicted tumor cell densities at t_i, we use a simple thresholding method. Given that the difference between the values on two subsequent tumor contours is not significant, the threshold value is chosen as the average value on the tumor contours at time t_{i-1}.

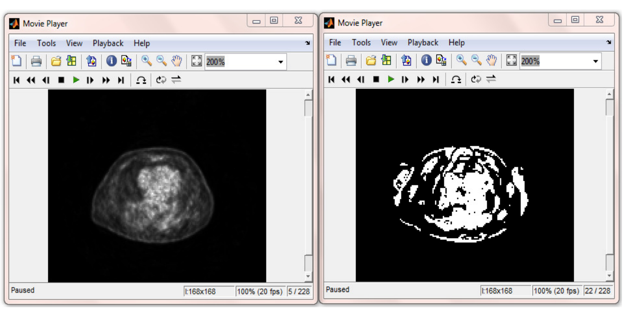

Fig 2: Advection done by 3D-optical flow through tumor

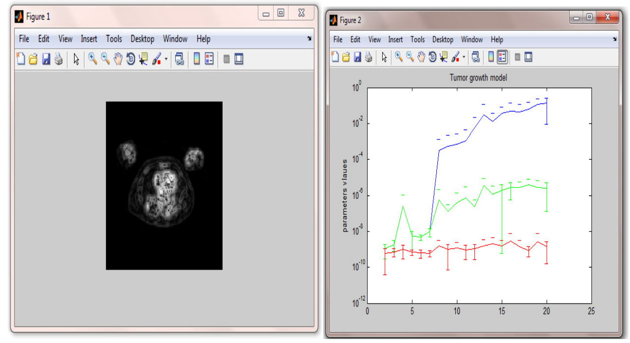

Fig 3: Tumor growth modeling

In original experimental setup, Error rates (%) are obtained by where training is done with rotations 0, 30, 45 and 90 degrees.

II. Conclusion

In this research, the technique was used to estimate the lung tumor growth model and its variations. The proposed model used to estimate a growth model with good accuracy and obtain thresholding on predicated and observed images used to define a lung tumor contour under global constraints.

Then the proposed method used to value the tumor growth model based on ADR equation with LBP intensity features are employed to simulate the tumor growth model. A performant algorithm used to estimate the parameter on patient specific model during radiotherapy in positron emission tomography. The grayscale rotation invariant method with LBP pattern based on intensity based features are employed to estimate the growth model influenced of evaluating the advection, proliferation and treatment terms. Thus the mathematical model implies the lungs tumor growth and obtains optimization between predicted images and estimates the parameter values.

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