Particle Filter Algorithm For Robotized Surgery

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Abstract- *The human respiratory movement affects the accuracy of the robotized radiotherapy treatment for lung cancer. To reduce the influence of respiratory movement, real time tracking of the tumor in respiratory system can be developed using tracking algorithm. By the established prediction the beam can be adjusted. The tracking algorithm used here is particle filter with UT modelling. Initially the particle filter algorithm is used and a probability correlation is drawn based on a UT transform. The result of the mentioned two steps gives the location of the tumor during the respiratory movement. The effectiveness and accuracy of particle filter algorithm based on UT transform is verified by error analysis. The experiment results proved that it has stronger robustness and higher prediction precision compared with the linear estimation and the traditional particle filter for a real time tracking of the tumor location*

Keywords- Respiratory movement; Radiosurgery robot; Particle filter; Tumor tracking; UT transform

I. INTRODUCTION

Treatment of lung cancer can be done by surgery, chemotherapy or radiosurgery. Surgical treatment is a traditional method leading to many risk and surgical complications. In chemotherapy, a minimum number of drugs or medicines is injected into the human body which can harm the other normal tissues present around the tumor.

During a respiratory movement the patients breath causes the correlative tumor movement in abdomen and thorax thereby changing the location and movement of the tumor. If the target area is irradiated with high dose for a long time, it is prone to cause normal tissue complications, which means a bad treatment effect.

In the traditional tracking of tumor, the method establishes a correlation model between the internal tumor and the external marker to apply the prediction algorithm for the tumor location. The commonly used prediction algorithms include linear extrapolation, artificial neural network, Kalman filtering, fuzzy control.

In recent years, some researchers took extended Kalman filter (EKF) algorithm into tumor prediction and obtained good prediction results. However, the EKF can only deal with Gaussian distributed noises, and need to linearize the nonlinear system model, which will introduce a larger model error additionally. On the contrast, the particle filter can handle the state estimation problem under the nonlinear and non-Gaussian dynamic system compared with the extended Kalman filter.

Since the tumor and marker placed on the patient’s body keep changing periodically, the parameters of the correlation model drawn also keeps changing accordingly. the sensor noises and modeling uncertainty are taken into consideration, and then a probabilistic correlation model is established based on UT transformation, which will be used in the particle filter to predict the tumor position.

II. INTODUCTION TO PARTICLE FILTER ALGORTHM

The particle filter algorithm uses particle set to describe probability that handles all non-Gaussian distributed noises. It extracts random particles from its posterior probability to express the state distribution.it can be applied on any nonlinear system for optimal estimation. Particle filters implement the prediction-updating updates in an approximate manner. The samples from the distribution are represented by a set of particles; each particle has a likelihood weight assigned to it that represents the probability of that particle being sampled from the probability density function.

2.1.1. Bayesian Estimation and sample filters

The Bayesian approach allows probability to represent subjective uncertainty or subjective belief. It fixes the data and instead assumes possible values for teta. Particle filter is a kind of Bayesian estimation method, which converts the target state estimation problem to posterior probability density to be solved by Bayesian formula and then use posteriori probability density to obtain expected value of function to get the optimal estimation of target state. Assume that the system state equation and measurement equation are as follows: Assume that the system state equation and measurement equation are as follows:

$$x_k = f_k\,(x_{k-1}, w_{k-1}) \text{ \_\_\_\_\_\_\_ } (1)$$
$$y_k = h_k\,(x_k, v_k) \text{ \_\_\_\_\_\_\_\_\_\_ } (2)$$

Assuming that the probability density function p(*xk-1|y1: k-1*) at *k-1* moment is known, the prediction equation is used to get the probability *p*(*xk|y1:k-1*) of *xk* from the probability density *p*(*xk-1|y1:k-1*):p(xk|y1:k–1) = *ƒ* p(xk|xk–1)p(xk–1|y1:k–1)dxk–1 __ (3)

The worst defect of sampling is particle degradation, namely, after a few iterations, some particles' weights become small and some particles weights become large. The number of effective particles becomes less and less along with the filtering process goes, thus to cause decline in performance.

III. COMPARISON OF METHODS

Now it is the time to articulate the research work with ideas gathered in above steps by adopting any of below suitable approaches: When we use tracking algorithm for tumor location, a correlation model is derived for measuring the values of variables.

Traditional model correlational model

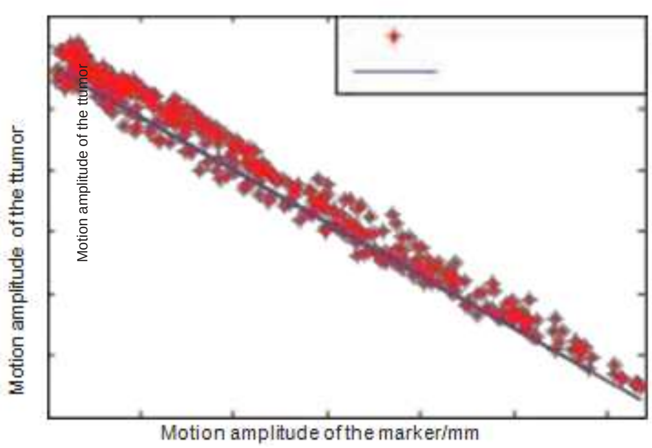

FIGURE- 1

It can be seen from the diagram that the tumor location and the external marker model forms a linear model. This is used widely for its strong simple structure, strong robustness and good stability. During the treatment, 3 markers are placed on the human body which creates three different correlational model which are independent to each other. The goal of the tumor tracking is to provide an optimized model considering the developed correlational model by 3 markers.

UT transform with correlation model

Unscented transform is a mathematical function applying a given nonlinear function into a probability distribution with respect to some finite set.

Assumes that the correlation model is *zk*=*h*(*xk*), where *xk* is tumor respiratory movement data in vivo and *zk* is markers' motion data in vitro at time instant *k*. *h*(.) is the fitted correlation model, which is described as follows:

$$h = g\,(x, z)$$

These are calculated in terms of means and variance with the help of sigma points. The nonlinear function is applied to each and every point present in the state space model.

The covariance model can be obtained by,

$$P_y = \Sigma 2n\ m_i(h_i — h\hat{})(h_i — h\hat{})$$

Therefore, the correlation model based on UT transform is:

$$zk = h\hat{}(xk) = a\hat{}xk + b\hat{}xk + vk$$

VI. EXPERIMENT ANALYSIS

The particle filter creates a progress model that estimates the state in previous time and current time (location of tumor in previous time and present time) and creates and observational model that draws the connection between system state and observed value at that time (tumor and surface marker).The breathing model continuously updated in the prediction process .The two phases are modeled and predicted independently to draw a correlational model,

When the correlational model is applied in the linear estimation algorithm, in the prediction results the particle filter algorithm in the probabilistic model is more accurate than the one formed with linear model since the error of the linear prediction is larger.

To analyze the prediction error more clearly,the difference between prediction value and actual value of each data point was calculated, and then the average of each breathing cycle error, finally we calculate the difference of cycle error between the two prediction algorithms. If the error difference is larger than zero, the prediction error of the particle filter algorithm based on the probabilistic model is smaller; otherwise, the prediction error of the proposed method is larger.

TABLE- 1

Methods / Errors	Linear prediction	Traditional model based particle filter	Probabilistic model based particle filter
Mean(mm) 2	2.2912	0.6601	0.6471
Variance (mm)	1.0489	0.1003	0.0986

V. DISCUSSIONS

From the experiment and analysis, linear prediction can also be used for real time tracking of the tumor location, but applying probabilistic model is more advantageous. Both traditional model and probabilistic model provides good prediction value when applied over the particle filter algorithm. But when considering the experimental error, particle filter based on probabilistic model has advantages, with more error reduction the treatment beam can be adjusted more accurately. This will reduce the incidence of complications and improve the survival rate of patients.
The error variance of the algorithm is the smallest, which means that it has higher robustness. The particle filter is suitable for any state space model, which can adapt to the abnormal change of the measured value.

However, there are many problems need to be considered when using the algorithm to predict respiration motion. In the experiment, we found that combining UT transformation modeling with particle filter algorithm leads to an increase in computation amount and causes longer prediction time. Since the medical robot system has a fixed delay time in the treatment of lung cancer, it is necessary to make a balance between accuracy and efficiency when use the particle filter algorithm based on the probabilistic model.

VI. CONCLUSIONS

The particle filter algorithm based on Bayesian estimation has its unique advantages in dealing with the state filtering of nonlinear and non-Gaussian systems. Many satisfactory results have been achieved in recent years. The respiratory correlation model is the basis of the particle filter algorithm developed for tumor tracking in robotized radio surgery. Traditional correlation model does not consider the sensor noises and uncertainty, so the modeling accuracy is not high. In this paper, the correlation model of probability is established based on UT transformation, based on which the motion of the tumor is predicted by particle filter, and compared with the linear prediction and traditional particle filter prediction algorithm. Experimental results show that the particle filter algorithm based on probability model can realize real-time tracking of tumor motion.

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