PREDICTIVE TRACKING FOR RESPIRATORY INDUCED MOTION COMPENSATION IN ADAPTIVE RADIOTHERAPY

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Abstract: This paper considers a compensation strategy for respiratory-induced tumour motion for adaptive radiotherapy using a controlled patient support system (PSS). A model predictive control (MPC) scheme for the PSS to track the tumour motion is proposed together with two methods for predicting tumour motion, including a Kalman filter and neural networks. Simulation results using a clinical data set consisting of 27 traces of respiratory motion show the potential of the proposed control strategy.

Keywords: Adaptive radiotherapy, Kalman filter, model predictive control, neural networks, tracking control, tumour motion.

1. INTRODUCTION

Radiotherapy aims to precisely deliver a lethal dose to tumours while minimizing radiation dose to the surrounding healthy tissues. Tumour movement is a challenge for achieving this objective. Respiration induces significant movement of tumours in the vicinity of thoracic and abdominal structures (Malone *et al.* 1999, Ross *et al.* 1990, Seppenwoolde *et al.* 2002, Suramo *et al.* 1984). A classical approach to accommodate the uncertainty of tumour location due to respiration is to add a relatively large planning target volume (PTV) margin to the clinical target volume (CTV) (McKenzie 2000, van Herk *et al.* 2000, van Herk 2004). A larger volume is thus irradiated to ensure adequate dose coverage of the tumour. This causes increased healthy tissues complications and the dose that can be delivered to a tumour is thus limited by the tolerance of the healthy tissue.

Several methods have been developed to increase tumour localization accuracy during irradiation. Breath-holding (Hanley *et al.* 1999, Mah *et al.* 2000) is a method to minimize the range of respiratory tumour motion. Respiratory gating is proposed to reduce tumour localization errors during irradiation by limiting the radiation exposure to a portion of the breathing cycle (Ohara *et al.* 1989, Kubo and Hill 1996). A sophisticated method is an adaptive radiotherapy scheme using a real-time tumour tracking strategy to synchronize the radiation beams with the moving tumour. A dynamic multi-leaf collimator (MLC) approach is proposed in (Keall *et al.* 2001, Neicu *et al.* 2003). In (Schweikard *et al.* 2000), a robotic arm is used to move the accelerator that produces the radiation beam.

In this paper an approach involving a controlled patient support system (PSS) to automatically reposition the patient in order to keep the moving

tumour in the path of the radiation beams is considered. A feasibility study for such an approach has been reported in (D'Souza *et al.* 2005). The PSS-based approach has an advantage in that it is potentially able to compensate 3D motion of the tumour, whilst a MLC-based approach is only able to compensate 2D motion. Furthermore, the approach only requires basic modification of the currently available PSS technology and retains the existing gantry-based treatment machine, which is a less expensive and more efficient option compared to the robotic-arm-based approach that needs a new machine configuration.

The current work focuses attention on the control strategy for the PSS to compensate for respiratory tumour motion, which is not considered in (D'Souza *et al.* 2005). A control scheme consisting of a model predictive controller (MPC) and a prediction algorithm to predict future tumour position based on current tumour position measurements is proposed.

The remainder of the paper is organised as follows: In Section 2 a model of a clinical PSS is described. Section 3 presents a proposed control scheme whilst its verification by simulation is presented in Section 4. Conclusions are given in Section 5.

2. MODEL OF PATIENT SUPPORT SYSTEM

Simulink and SimMechanics are the software tools exploited to implement a mechanical model of the longitudinal, lateral and vertical axes of the PSS (Spriestersbach *et al.* 2004). Each SimMechanics block represents mechanical or electromechanical parts such as rigid bodies, joints, drivers, sensors, actuators etc. The shape, mass, centres of gravity and inertia tensors of the rigid bodies are defined using information from manufacturers. The rigid bodies are then linked together using various means, including welds, joints and gears. Electromechanical blocks of SimMechanics such as sensors or actuators can be interfaced with Simulink blocks, so that Simulink blocks are used to model the electrical components of the PSS. Actuator inputs represent drive signals for the motors, which are equivalent to the input voltage that is applied. The output signals represents the actual axes displacement in mm.

To validate the developed model, measurements were obtained using actual RT equipment. Data acquisition devices comprising a 6024E PCMCIA card and a signal conditioner SC2345 from National Instruments were used. The measurement device was connected to the output of a pulse-width modulated (PWM) amplifier to measure the signals to the motors to drive the PSS along its axes (the longitudinal axis is considered here).

Signals from potentiometers measuring the position of the PSS were simultaneously logged. To gauge the likely performances, the PSS was loaded with a range of masses (40, 68 and 94kg) to simulate the effect of different patient loads. Signals obtained from motors corresponding to the actual system, after filtering and resampling, were used as inputs to the SimMechanics model. The output (position) of the actual system and output of the simulation were then compared. It was found that the model was able to adequately replicate the behaviour of actual system.

The SimMechanics model was developed for the purpose of simulation and includes nonlinearities such as friction and stiction, quantization of measurements, backlash and input saturation. However, for the purpose of model-based controller design, nonlinearities are removed resulting in a simplified linear model, which is considered to be realistic.

3. PROPOSED CONTROL SCHEME

In this section, the proposed MPC control scheme designed in order for the PSS to track respiratory tumour motion is described. The main reason to choose a MPC control scheme is that it is able to accommodate the latencies of the controlled plant and it also provides the possibility to constrain the response such as restriction in the allowed actuator velocity and acceleration (Maciejowski 2002). Furthermore, MPC has been widely adopted in industrial applications. The novelty in the proposal scheme is in the generation of the reference signal required by MPC. The reference signal is required to be predicted in advance in order, for the controller to take advance action, thereby accommodating delays and latencies in the overall system.
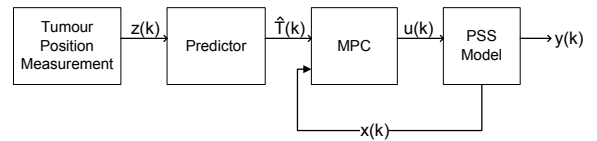

Fig. 1. Schematic of proposed control system

$z(k)$ represents the current tumour position, $\hat{\mathcal{T}}(k)$ is a vector of predicted tumour positions, $y(k)$ and $u(k)$ are PSS output and input, respectively, and $x(k)$ denotes state variable feedback.

3.1 Respiratory motion prediction

Respiratory movement can be either regular or irregular. Regular breathing is defined by periodic exhalation (deflation of lung) and inhalation (expansion of lung) with more time spent in exhale

than inhale. Irregular breathing is illustrated by either additional states between or within cycles or changes in frequency and amplitude of the motion. In addition to the cycle-to-cycle changes data are corrupted with noise, due to the acquisition process of imaging devices.

Various proposals have been put forward for predicting such motion, see for example (Sharp *et al.* 2004, Vedam *et al.* 2004, Isaksson *et al.* 2005, Putra *et al.* 2006). In this work two methods are investigated: a Kalman filter with a constant velocity model and a set of neural networks using a regularization procedure. Both approaches aim to generate predicted reference trajectories that are suitable for a receding horizon MPC scheme. The predicted trajectories are then utilized to determine an optimal control which is is calculated based on a minimization of future predicted tracking errors.

Kalman filter

The Kalman filter (KF) is an optimal state estimator of linear systems that minimizes the mean of the squared error of the estimation (Kalman 1960). The recursive feature of the KF makes it suitable for online prediction. The KF algorithm consists of prediction and correction steps. Assume that the evolution of the respiratory motion over a short-period of time can be described by

$$\begin{aligned} \xi(k) &= F\xi(k-1) + Gv(k-1) \\ z(k) &= H\xi(k) + \omega(k) \end{aligned} \tag{1}$$

where $\xi = \begin{bmatrix} \xi_1 \\ \xi_2 \end{bmatrix}$, $F = \begin{bmatrix} 1 & \Delta t \\ 0 & 1 \end{bmatrix}$, $G = \begin{bmatrix} \Delta t \\ 1 \end{bmatrix}$ with ξ_1 and ξ_2 denoting the position and the velocity of the tumour, respectively, Δt is the sampling period, z the measured tumour position, $H = \begin{bmatrix} 1 & 0 \end{bmatrix}$, v and w are the process and measurement noises which are uncorrelated zero-mean Gaussian white noises with covariance matrices Q_v and R_ω, respectively. The KF for the tumour position prediction is as follows.
For given $\hat{\xi}(k|k-1)$, $P(k|k-1)$ and $z(k)$ compute

$$\begin{aligned} r(k) &= z(k) - H\hat{\xi}(k|k-1) \\ S(k) &= HP(k|k-1)H^T + R_\omega \\ K(k) &= P(k|k-1)H^T S^{-1} \\ \hat{\xi}(k|k) &= \hat{\xi}(k|k-1) + K(k)r(k) \\ P(k|k) &= P(k|k-1) - K(k)S(k)K(k)^T. \end{aligned}$$

Next prediction is given by

$$\hat{\xi}(k+1|k) = F\hat{\xi}(k|k), \ \hat{z}(k+1|k) = H\hat{\xi}(k+1|k)$$
$$P(k+1|k) = FP(k|k)F^T + GQ_vG^T.$$

To obtain Hp future samples of tumour position as required by MPC the following computations are added to the prediction step

$$\begin{aligned} \hat{\xi}(k+j|k) &= F^j\hat{\xi}(k|k), \\ \hat{z}(k+j|k) &= H\hat{\xi}(k+1|k), \text{ for } j = 2, .., Hp. \end{aligned}$$

Neural network

A neural network (NN) is a nonlinear model which is trained to 'learn' a relationship between input and output data. If sufficient input/output data is available, the training of a NN provides a useful 'black-box' approach to model input-output mappings with little or no requirement for *a priori* knowledge of the process. They have also found use in predictive control (Haykin 1999, Tsoukalas and Uhrig 1997, Liu 2001).

In this paper H_p parallel time series prediction multi-layer perceptron neural networks (TSP MLPs) (Tsoukalas and Uhrig 1997) are used to produce a vector of predicted future marker positions. The NN architecture is optimized off-line deterministically using the first portion corresponding to 10 s of each data set. An optimal architecture is then implemented throughout. The same approach is taken by (Sharp *et al.* 2004). The resulting NN architecture has 7 inputs, 9 hidden neurons and a scalar output $\equiv r(k + i|k)$. Each hidden neuron uses the tansig function $y = (e^v - e^{-v})(e^v + e^{-v})^{-1}$, where v and y represent the neuron input and output respectively, while the output neuron is linear. A hybrid training method is used which combines a regularization algorithm (RA) with conjugate gradient backpropagation (CGBP) (Haykin 1999). The RA uses a weight decay function F_w, which is the mean-square of the total number of weights and biases, $w_j, \ j = 1, 2, \ldots, W$, in the NN i.e. $F_w = \frac{1}{W}\sum_{j=1}^{W} w_j^2$. This is added to the training performance function

$$F = \frac{1}{N}\sum_{i=1}^{N}(z_i - r_i)^2 \tag{2}$$

where z_i, r_i are the observed target data and NN output respectively, to give an energy function defined as

$$\begin{aligned} F_r &= \alpha F + (1-\alpha)F_w \\ &= \frac{\alpha}{N}\sum_{i=1}^{N}(z_i - y_i)^2 + \frac{1-\alpha}{W}\sum_{j=1}^{W}w_j^2 \end{aligned} \tag{3}$$

where $0 < \alpha < 1$ is a regularization parameter which controls the amount of influence exerted by F_w on the energy function. CGBP employs a line search to find successive local minimum values of F. At each local minimum, the algorithm is reset by calculating a new search direction until the algorithm either converges or is terminated by a suitable criterion e.g. time limitation or validation error. CGBP is used to train a static MLP in (Sharp *et al.* 2004). NN training is carried out using the following procedure

(1) Train with the first 5 s of data using regular-ization.
(2) Subsequently up-date at intervals of 1s lim-iting training time to a maximum of 0.1 s, using the latest 5 s of data. This ensures that at least one complete breathing cycle is used for training at each update. Due to the longer time required for regularization convergence, only CGBP is used for on-line updating.

3.2 Model Predictive Controller

In MPC, the controlled input is calculated such that the system model follows a given future reference signal whilst optimizing a defined cost function. The cost function to be minimised is (Maciejowski 2002):

$$
V(k) = \sum_{i=1}^{H_p} \left|\left|\hat{y}(k+i|k) - \hat{r}(k+i|k)\right|\right|^2_{Q(i)}
$$
$$
+ \sum_{i=1}^{H_u} \left|\left|\Delta\hat{u}(k+i-1|k)\right|\right|^2_{R(i)}
\tag{4}
$$

where: H_p and H_u are prediction horizon and con-trol horizon, respectively; $\hat{y}$ and $\hat{u}$ are predicted output and input, respectively; $\hat{r}$ is a reference to be followed provided by the predictor; $\Delta = 1 - z^{-1}$ with z^{-1} denoting the backward shift operator, and $Q(i)$ and $R(i)$ are controller weights.

At each sample step k the predictor calculates a vector of predicted tumour positions $\hat{\mathcal{T}}(k) = \{\hat{r}(k+1|k), \ldots, \hat{r}(k+i|k), \ldots, \hat{r}(k+H_p|k)\}$ which is fed to MPC as a reference trajectory to be tracked. In this paper the latency of organ motion monitoring was assumed to be zero for simplicity. If it was n samples, then the vector of predictions would be $\hat{\mathcal{T}}(k) = \{\hat{r}(k+1+n|k), \ldots, \hat{r}(k+i+n|k), \ldots, \hat{r}(k+H_p+n|k)\}$. The prediction of tumour position $\hat{r}(k+i|k)$ is typically more accurate than $\hat{r}(k+j|k)$ for $j > i$. Hence $\hat{y}(k+i|k) - \hat{r}(k+i|k)$ shall be of greater importance than $\hat{y}(k+j|k) - \hat{r}(k+j|k)$, and the controller weights are chosen such that $Q(i) = (H_p - i + 1)^2$. It is also assumed that $\Delta\hat{u}$ should be equally penalised for the whole control horizon, and the ratio of penalisation of predicted tracking error and penalisation of $\Delta\hat{u}$ should remain constant regardless of H_p and H_u, leading to:

$$
\frac{\sum_{i=1}^{H_p} Q(i)}{\sum_{i=1}^{H_u} R(i)} = constant
$$

$$
\forall (i,j \in \langle 1, H_u \rangle) \ R(i) = R(j)
$$

therefore

$$
R(j) = \rho \cdot \frac{\sum_{i=1}^{H_p} Q(i)}{H_u}, \ j \in \langle 1, H_u \rangle
\tag{5}
$$

where ρ is a scalar valued tuning parameter.

The cost function given in Equation (4) is linear quadratic. It is therefore possible to analytically obtain an optimal control action denoted $u(k)_{opt}$, and this value is computed using a least-squares approach (Maciejowski 2002).

4. SIMULATION STUDIES

To evaluate the proposed control scheme for dif-ferent horizons and sampling frequencies, simula-tion studies were carried out using a clinical data set consisting of 27 traces, each of 200s respira-tory motion, collected at Virginia Commonwealth University, USA (George et al. 2006). Different horizons are tested to assess their influence on the tracking performance. Although the data set corresponds to the motion of external markers and not the tumour itself, it has been shown that for some parts of the body (e.g. pancreas) there is a close correlation between motion of external markers and actual organ motion (Murphy 2004). In this paper it is assumed that the motion of external markers represents motion of the tu-mour. Characteristics (amplitude and period) of the data is presented in Figure 2.
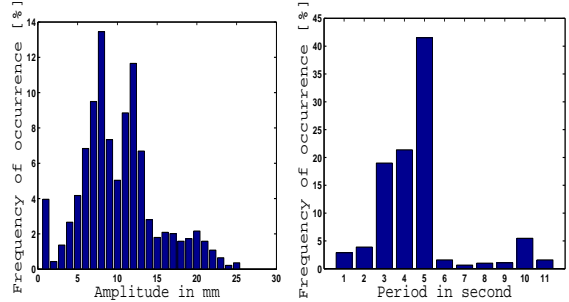

Fig. 2. Histograms of amplitude and frequency of the respiratory motion data

The time of computation of reference $\hat{\mathcal{T}}(k)$ and $u(k)_{opt}$ is assumed to be 10ms. The time of propa-gation of the control signal via a network to motor drives is assumed to be 10ms.

A total of 20 scenarios were simulated for con-troller sampling rates $f_c = \{10Hz, 15Hz\}$ and different prediction horizons. The maximum pre-diction horizon was 0.5 second. Original motion data was sampled at 30Hz, thus it was resampled online within the predictor to match the sampling rate of the controller.

The performance of the proposed control scheme utilizing the two prediction methods was bench-marked against a PID controller and MPC with an ideal predictor (which reads data from the file in advance). The PID controller was initially tuned for a linear PSS model using a pole-placement method. It appeared, however, that the control action was too high for the nonlinear simulation

Table 1. Results of simulation studies

Crit.	PID	Ideal pred	MPC with predictor																				
			Kalman Filter Predictor										Neural Network Predictor										
			$f_c = 15Hz$						$f_c = 10Hz$				$f_c = 15Hz$						$f_c = 10Hz$			
			H_p						H_p				H_p						H_p			
			2	3	4	5	6	7	2	3	4	5	2	3	4	5	6	7	2	3	4	5
$RMSE$	0.87	0.18	0.56	0.46	0.44	0.44	0.44	0.45	0.53	0.49	0.48	0.48	0.29	0.25	0.24	0.25	0.24	0.26	0.38	0.35	0.34	0.33
Var	0.77	0.03	0.31	0.21	0.20	0.19	0.20	0.20	0.28	0.24	0.23	0.23	0.08	0.06	0.06	0.06	0.06	0.06	0.14	0.12	0.12	0.11
$OUT_{0.2}$	78.9	15.0	68.1	63.0	60.0	60.5	59.8	59.5	68.5	66.5	65.4	64.5	35.5	27.5	24.6	23.2	21.9	21.1	41.3	36.8	35.0	33.7
$OUT_{0.5}$	54.6	0.5	28.5	20.2	17.2	17.5	17.1	16.7	28.0	25.0	23.3	22.4	5.2	3.3	2.6	2.3	2.0	1.8	9.1	7.2	6.4	5.9
OUT_1	24.8	0.2	5.5	1.9	1.3	1.3	1.2	1.2	4.6	3.2	2.6	2.4	0.7	0.5	0.5	0.4	0.4	0.4	1.7	1.5	1.4	1.4
OUT_2	2.4	0.1	0.4	0.2	0.2	0.2	0.2	0.2	0.3	0.3	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.1	0.4	0.4	0.4	0.4

model due to the presence of torque limit (input saturation), therefore lower gains were required. For simulation with an ideal predictor the setup was: $H_p = H_u = 7$, $f_c = 15Hz$. The performance criteria to evaluate the controllers are:

- Root mean square error ($RMSE$) and variance of tracking error (Var)
- Percentage of time of absolute tracking error being larger than a threshold (OUT_{thr}), with absolute thresholds of 0.2mm, 0.5mm, 1mm and 2mm.

Evaluation of the proposed control scheme performance started after 10 seconds of each trajectory to allow the predictor to tune [1]. The performance criteria were calculated using tracking errors of all the 27 trajectories and the results are presented in Table 1.

It was found that the proposed control scheme outperformed the PID controller for every performance criteria. The performance of MPC + KF was similar for $f_c = 15Hz$ and $f_c = 10Hz$. However, the performance of MPC + NN was significantly degraded for $f_c = 10Hz$ compared to $f_c = 15Hz$. The performance of MPC + NN at $f_c = 15Hz$ and $H_p = \{6, 7\}$ is comparable to the case of MPC + ideal predictor and is better than the performance of MPC + KF. However, MPC + NN tends to produce large tracking errors at $f_c = 10Hz$ more often compared to MPC + KF (c.f. OUT_2 of KF and NN at $f_c = 10Hz$). It was also found that the performance of MPC with both prediction methods was always improved for larger H_p.

5. CONCLUSIONS

This paper has presented work in progress concerning the compensation strategy of respiratory induced tumour motion for adaptive radiotherapy using a controlled patient support system. A model predictive control scheme with a reference signal to be tracked (future tumour positions)

provided by a Kalman filter or a set of neural networks has been developed. The tracking performance of the proposed control scheme has been tested by means of simulation studies using a clinical data set consisting of 27 traces of respiratory motion. It was found that the MPC control scheme consistently outperformed a manually tuned PID controller. The tracking errors of the MPC with the NN was significantly smaller than the MPC with the KF in terms of RMSE. However, the percentage of large tracking errors was greater for MPC with the NN compared to MPC with the KF when the controller was sampled at 10Hz. Further work is on going to fully evaluate the limitations of the proposed schemes.

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[1] KF predictor requires only 2 samples for initialization, but the NN predictor requires several seconds to 'learn'.

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