Marker-less Intra-Fraction Organ Motion Tracking – A Hybrid ASM Approach

Y Su 1, M H Fisher 1, R S Rowland 1
1 School of Computer Sciences, University of East Anglia
Norwich, Norfolk, NR4 7TJ, United Kingdom
Phone: +44 (0)1603 593287, Email: sy@cmp.uea.ac.uk

Abstract – External beam radiation therapy attempts to deliver a high dose of ionizing radiation to destroy cancerous tissue, while sparing healthy tissues and Organs at Risk (OAR). Recent advances in Intensity Modulated Radiotherapy Treatment (IMRT) call for a greater understanding of uncertainties in the treatment process and more rigorous protocols leading to greater precision in treatment delivery. The degree to which this can be achieved depends largely on the cancer site. The treatment of organs comprised of soft tissue (e.g. in the abdomen) and those subject to rhythmic movements (e.g. lungs) cause inter and intra-fraction motion artifacts that are particularly problematic. Various methods have been developed to tackle the problems caused by organ motion during radiotherapy treatment, e.g. Real-Time Position Management (RPM) Respiratory Gating (Varian) and Synchronized Moving Aperture Radiation Therapy (SMART), developed by researchers at Harvard medical school. The majority of the work focuses on tracking the position of the pathologic region, with the intra-fraction shape variation of the region being largely ignored. This paper proposes a novel method that addresses both the position and shape variation caused by the intra-fraction movement. This approach is seen able to reduce the margin of Clinical Treatment Volume (CTV), hence, spare yet more surrounding healthy tissues from being exposed to radiation and limiting irradiation of OAR.

Keywords – Intensity Modulated Radiotherapy Treatment (IMRT), Clinical Treatment Volume (CTV), Region of Interests (ROI), Organs at Risk (OAR), Treatment Planning System (TPS), Real-Time Position Management (RPM), Image Guided Radiotherapy Treatment (IGRT), Cone-Beam Imaging (CBI), Radiotherapy Treatment Planning (RTP), Digitally Reconstructed Radiograph (DRR), Synchronized Moving Aperture Radiotherapy (SMART), Average Tumor Trajectory (ATT), Artificial Neural Network (ANN), Linear Accelerator (Linac), Active Shape Model (ASM), Active Appearance Model (AAM), Active Contour Models (ACM), Electronic Portal Imaging Devices (EPID), Hidden Markov Models (HMM), Beam’s Eye View (BEV), Multi-leaf Collimator (MLC), Principle Component Analysis (PCA), 4-Dimensional CT (4DCT)

I. INTRODUCTION

A. Objectives of the Work

Recent research works, addressing intra-fraction organ motion, normally adopt surface or embedded markers to track the position of the Region of Interests (ROI). Although much work has been published on the effect of intra-fraction organ motion and techniques compensating for it, the problems caused by shape variations in the tumor has been largely ignored. In this work, we developed a novel method to enable the accurate tracking of intra-fraction organ shape as well as position variations. We propose to use a system in which two extra X-ray imagers are needed for sampling purpose before the treatment, a Hybrid Active Shape Model (ASM) tracker is then build using the acquired training samples. This model is able to learn from the training data, and interpret the current shape and position using local monitoring image evidence. During real-time treatment, only one extra X-ray imager is required, in addition to the treatment Linear Accelerator (Linac), to monitor the real-time shape and position variation. The approach is seen able to reduce the margin of Clinical Treatment Volume (CTV), hence, spare more surrounding healthy tissue from radiation and protect Organs at Risk (OAR).

The rest of Section I gives readers a brief background information of the start-of-art systems and technologies in the area. Section II explains the proposed approach in details. The preliminary results are presented in Section III. Section IV concludes on the pros and cons of this novel method as well as sets out work plan for the near future.

B. State of The Art Commercial Systems

In recent years, major manufacturers and research institutes have came up with various state-of-the-art systems to tackle the intra-fraction motion.

Respiratory gating is one of the main stream approaches. It integrates beam control software into the Treatment Planning System (TPS). Research work on respiratory gating has been carried out by various groups [1,2]. Varian’s Real-Time Position Management (RPM) Respiratory Gating system is a state-of-the-art commercial system launched in 2003 (ref. Figure 1). The system infers the position of the tumor and ORA by tracking retro-reflective markers, affixed to the patients chest, in camera images. At the treatment planning stage a virtual window is defined. During the delivery of radiation, beam is only switched on when the tumor, identified by the marker, passes through that region defined by the virtual window [2].

Fig. 1 Schematic of Varian’s Real-Time Position Management (RPM) Respiratory Gating system [2, Courtesy of Varian Medical Systems]
However, due to the fact that the beam is only turned on for a relatively shorter period, to make sure the tumor receive prescribed dose, the treatment period is inevitably prolonged. Additionally, due to the lack of constant irradiation, the treatment result may be compromised.

Image Guided Radiotherapy Treatment (IGRT) is another complementary approach aimed at tackling the problem of inter-fraction motion. This approach commonly uses a so-called Cone-Beam Imaging (CBI) technique to acquire 3-D volumetric data immediately prior to treatment delivery. A degree of invariance to intra-fraction motion is achieved by co-registering this data set with that used by the TPS. A series of publications on CBI are found mainly subject to the research work carried out by Jaffray and his colleagues [3, 4, 5, 6].

Elekta, were amongst the first to market CBI systems after a period of testing in collaboration with the William Beaumont Hospital in Detroit, USA; the Princess Margaret Hospital in Toronto, Canada; the Christie Hospital, Manchester, UK; and the Netherlands Cancer Institute, Amsterdam, The Netherlands [7]. In their Elekta Synergy system, real-time CBI CT images are used to monitor the organ motion and patient positioning. The Elekta Synergy system is seen as an efficient mean to monitor organ motion, allowing for co-registration of CBI CT images and Radiotherapy Treatment Planning (RTP) data in real-time, immediately before treatment delivery (ref. Figure 2).

Varian has also developed a similar approach for IGRT called the iX medical Linac [8], shown in Figure 3.

Recent research work also addressed intra-fraction organ motion. Again, mainstream methods normally adopt surface or embedded markers to track the position of the Region of Interests (ROI). A series of research work, carried out at Harvard Medical School and Massachusetts General Hospital, represents this general trend. Among them, Neicu et al. introduced Synchronized Moving Aperture Radiotherapy (SMART). In it, tumor motion is represented by a sequence of 3D position data of a marker. The tumor aperture is acquired at the treatment simulation/planning stage. The Average Tumor Trajectory (ATT) is then derived and used to infer tumor motion; this is subsequently incorporated into IMRT leaf sequence. At the treatment delivery stage, the position of the marker is monitored and used to synchronize the treatment and the tumor motion [10].

Further investigations into the effect of lung motion have been carried out by Jiang et al. In their work, the researchers have investigated the problem caused by the fact that the phase of intra-fraction respiratory motion may potentially compromise the result of IMRT. Although results have shown that the problem is insignificant, the study did not address the potential damage to the surrounding normal tissue caused by the intra-fraction motion [11].

The treatment system latencies in dose delivery, including image acquisition, image processing, communication delays, control system processing, inductance within the motors, mechanical damping, etc, also need to be taken into consideration. Part of these problems have been addressed by Sharp et al. Various motion prediction algorithm has been investigated for tackling the system latencies, for example, linear prediction, linear extrapolation, Artificial Neural Network (ANN) and the Kalman filter [12].

Real time tracking of tumor motion without markers requires images that exhibit good contrast with respect to soft tissues. EPID images acquired during treatment are unsuitable for the task as they only show bony anatomy. Addressing this problem, Berbeco et al. designed an integrated radiotherapy imaging system with two diagnostic X ray sources mounted to the Linear Accelerator (Linac) gantry, these extra X-ray sources are used to produce diagnostic quality images. Using the stereo pair, this configuration is designed to obtain accurate 3D positional information of a marker, which infers a moving tumor in real-time [13].
The latest radiotherapy facilities have been on display in the ASTRO (American Society for Therapeutic Radiology and Oncology) Exhibition, November 5-9, 2006, Philadelphia. Among them, the Tracknife system from InitiaRT has presented a similar idea to our approach [14], the differences lay in that the actual tracking method used by Tracknife is still based on markers and seemingly using Electrical Portal Image Devices (EPID) images as a feedback to track the position change of the ROI in real time, while our approach is mark-less and take into account the shape variation as well as the position changes of the ROI, hence, is seen able to achieve more accurate tracking and spare more surrounding healthy tissue. However, the Multi-leaf Collimator (MLC) movement controlled by the moving organ aperture has been clearly demonstrated in the Tracknife presentation. Another interesting piece of equipment is the Siemens MV+kV Artist Linac, which has the ability of switching its radiation source between KeV and MeV [15]. A KeV source is a kV voltage level radiation source, which would not kill cancerous tissue, hence, is not used in the actual radiation treatment. However, it can produce relatively clearer diagnostic quality images. On the other hand, a MeV source is a MV voltage level radiation source, used in the actual treatment for killing cancerous cells. If a fluorescent panel is placed underneath the patient’s treatment bed, a series of EPID images can be obtained. These EPID images are normally used to evaluate the accuracy of treatment delivery against the treatment plan. Nonetheless, the resulting EPID images would be of much less quality to compare with the diagnostic images produced with KeV source. The Siemens MV+kV Artist Linac equipment, combined with an extra KeV X-ray imager, would provide the possibility of the data acquisition hardware configuration required in our method for both sampling and treatment process.

D. Unsolved Problems and Possible Solutions

Among all the above mentioned approaches, the problem, caused by shape variations in the tumor, has been largely ignored. In this work, we developed a novel method, which also uses a pair of extra KeV X-ray images. The differences, between our method and the one used by Berbeco et al [13], lay in that we only use two KeV imagers at the treatment simulation stage to obtain training data for the purpose of building a novel joint-parameter Hybrid Active Shape Model (ASM) model. During treatment, only one extra KeV X-ray source is needed to be placed at a monitoring angle that is different from the treatment beam angle. This method allows the shape as well as position variation of the ROI from treatment beam angle to be accurately tracked. The tracking results will then be used to control the MLC, details of the implementation can be found in section II.

A shape model is able to adapt itself to fit the data and in the context of organ tracking it is able to learn from prior information, and interpret the current shape using local image evidence. Several techniques for modeling shape have been proposed in the past [16]. The most popular approaches are summarized as follows.

Cootes et al. have developed a statistical model of shape and appearance called an Active Shape Model (ASM) and Active Appearance Model (AAM) respectively, to describe the shape and texture variations in a training set of images [17, 18, 19]. By calculating the appropriate parameters a best matching can be found between the synthesized model image and target image. The statistical models have been successfully applied in medical applications [20]. They have also furthered their research in statistical models for medical image analysis and computer vision [21, 22].

Active Contour Models (ACM) are physical models comprising a variety of forms, namely, snakes, deformable template, and dynamic contours [23]. Derraz et al. has introduced ACM into medical image segmentation [24].

II. PROPOSED APPROACH – HYBRID ASM TRACKING

This novel method enables the accurate tracking of intra-fraction organ shape variation as well as the intra-fraction position variation, it is seen able to reduce the CTV margin, hence, spare the surrounding healthy tissue from exposing to radiation beam to an larger extent, in other words, this method addresses the protection of OAR. Initially, respiratory motion will be targeted.

A. Hardware Configuration

In this approach, we propose to automatically track the ROI from a sequence of monitoring images with diagnostic quality. Firstly, after RTP but prior to treatment, a sampling phase is added to gather training data. Two diagnostic quality image sequences are acquired at this stage using two KeV X-ray imagers, positioned at two different viewing angles (ref. Figure 4a). During treatment, one extra KeV X-ray imager is mounted to the treatment gantry to monitor the shape and position variation of ROI (ref. Figure 4b) from the monitoring angle. The geometric configuration among the two KeV X-ray imagers and the subject, used at sampling stage, needs to match that among the Linac, the KeV X-ray monitoring imager and the subject during treatment (ref. Figure 4a-b).
An ASM model is built on each of the two synchronized training image sequences, and then a hybrid ASM model is developed to describe how the variation of the parameters in one ASM model maps to the parameter variation in the other. The term ‘Hybrid’ is used to describe this mapping technique. A schematic description of the Hybrid ASM approach is displayed in Figure 5.

In our approach, it is important to build a highly accurate mapping function between the two ASM models built on two image sequences of one object taken from two different viewing angles. Cootes et al. has introduced a coupled-view AAM [25], in which a small set of AAM models, each taken from a different viewing angle, are combined into a joint couple-view ASM model, a viewing angle function is learnt from the parameters of the set of separate ASM models, the resulting function is then used in constructing a model for a new viewing angle, which is not included in training set.

In the next step, let $r$ be the residual vector not explained by the orientation estimation. i.e.

$$r = c - (c + c_c \cos(\theta) + c_s \sin(\theta))$$

A model of the relationship between the model parameters of one view and those in another is built as follows. Let $r_j$ be the residual model parameters for the object in the $j^{th}$ image in view $j$. Assuming two viewing angles are used to obtain training data, a combined parameter vectors
$j_i = \left( r_{i1}^p, r_{i2}^p \right)$ is formed and a Principle Components Analysis (PCA) is applied on the set of $\{j_i\}$ to obtain the main modes of variation of the combined model,

$$j = \hat{j} + Pb$$  \hspace{1cm} (7)

A step-by-step implementation can be found in [25].

In our case, subjected to the limitation of the hardware configuration, only two viewing angles are available to provide training data, which is inadequate to provide enough angle variety in training samples. Give the advantage that in our case, the angle between the two viewing direction is fixed (ref. Figure 4), we came up with an alternative solution to correlate the two ASM models, in which another PCA is applied on the poses and weight vectors of each ASM model build on each image sequence.

First, let us denote the training image sequence from the monitoring angle as Sequence 1 and the ASM model built on this sequence as ASM1, the training image sequence from the treatment beam angle as Sequence 2 and the ASM model built on this sequence as ASM2.

After the two ASM models are built, each model is run on the corresponding training sequence to obtain a set of weight vectors and a set of pose vectors, $(B1, PS1)$ and $(B2, PS2)$ respectively,

$$B1 = \{ b_{i1} \} \quad \text{and} \quad PS1 = \{ pose_{i1} \}$$
$$B2 = \{ b_{i2} \} \quad \text{and} \quad PS2 = \{ pose_{i2} \}$$

where $i \in \{1, 2, ..., N\}$, $N$ is the total number of images in Sequence 1, which is the same as in Sequence 2 as the two sequence are synchronized. Details about the definition of weight coefficients and poses can be found in [20].

Then, a PCA analysis is applied on a combined parameter set, $\{j_i\} = (B1, PS1, B2, PS2) = \{ b_{i1}, pose_{i1}, b_{i2}, pose_{i2} \}$

The combined model is then derived as

$$j = \hat{j} + Pb$$  \hspace{1cm} (8)

where $\hat{j}$ is the mean of the combined parameter set, and $P_j$ is the matrix of the first $t$ eigenvectors, describing the modes of variation of the model parameters.

We define this model as the Hybrid ASM model, hereby denoted as ASMH, the ASMH uses the Grey Level Distribution Model of Sequence 1 and the real-time incoming image of the monitoring sequence to calculate the residual error for each iteration.

During the treatment, when the real-time monitoring image coming in, the ASMH iteratively optimize its weight vector $b$ so that the residual error between the current grey level profile of ASM1 and the incoming image reduces to a predefined tolerance level. Finally, the resulting joint parameter, $j$, is decomposed into a set of parameters $(b_{i1}, pose_{i1}, b_{i2}, pose_{i2})$, which is used to construct a set of model points to form the shape of the real-time Beam’s Eye View image (ref. Equation 1).

The resulting set of model points is then used to control the MLC leaves as to be shown in the following section.

D. MLC Control Process

The MLC is a panel placed below the radiation source, and the leaves of the panel can be controlled to form a hole, with a particular predefined shape, to allow the beam to go through. Figure 6 depicts the setting of the radiation source, the MLC panel, and the subject.

When simulating the MLC control, the total number of leaf-pairs and the leaf height are treated as known parameters. We simplify the process by assuming that each contour section between every two model points is a straight line. Simple trigonometry is then applied to calculate the intersection point between either the top or the bottom level of each leaf and the contour section.

Firstly, found the lowest and highest $y$ value among all the model points, the information will be used to define the lowest and highest leaf pair. Then, the $y$ value covered by each leaf-pair, between the highest and the lowest pair, would be calculated, then, all model points whose $y$ value is covered by the current leaf pair will be identified. For each leaf-pair, the leaf-most model point and right-most model point will be chosen, the line session between them and their adjacent model points will be used to calculate the intersection point with the leaf. Figure 7 illustrates the MLC control process.

![Fig. 6 The setting of Radiation source, MLC panel and subject](image1)

![Fig. 7 MLC control trigonometry](image2)
We denote $H$ as the Height of each leaf, $Y_i^t$ as the top level of the $i^{th}$ pair of leaves on $y$ axis, $Y_i^b$ as the bottom level of the $i^{th}$ pair of leaves on $y$ axis, $X_i^r$ as the right end of leaf $Li$ on $x$ axis, $X_i^l$ as the left end of leaf $Ri$ on $x$ axis, and $M$ as the total number of pairs of leaves, in the situation shown in Figure 11, $M = 30$.

Take model point $P_t = (x_t, y_t)$ and $P_2 = (x_2, y_2)$, as shown in Figure 11, if $m^{th}$ leaf-pair is to be used to approach the contour section between $P_1$ and $P_2$, the position of the top edge of the leaf is calculated as

$$Y_m^t = mH$$

Then, the position of the left leaf, to be used, can be calculated as follows

$$X_m^l = \frac{(mH - y_1)(x_1 - x_2) + x_1}{y_1 - y_2}$$

III. RESULTS TO DATE

An existing ASM model, which was previously developed at UEA for face tracking, has been modified to carry out real-world ROI tracking. The results are displayed in Figure 8.

![Fig. 8 Organ tracking (contour) using ASM (active shape model)](image)

Given difficulties to access and alter a Linac machine with our proposed configuration, the proposed Hybrid ASM mapping approach has been carried out in a simulation environment using simulated coupled-view testing sequences. The testing data is generated using a fast volume rendering package – 3DView [26, 27], available within our group.

First, a 3D object is reconstructed from a real set of CT volume data, then, simulated periodic movement is applied to the reconstructed 3D volume, finally, the moving 3D volume is projected onto two viewing planes from two different viewing angles. A snapshot of the virtual data generation environment is displayed in Figure 9. The simulation environment and a process of the MLC control using the Hybrid ASM mapping are displayed in Figure 10.

![Fig. 9 a) Simulation environment for generating testing data, a) with beam configuration) b) with organ movement configuration](image)

![Fig. 10 ASM Hybrid MLC control using simulated coupled-view sequences](image)

IV. 4. CONCLUSION AND FUTURE WORK

Compared with other organ tracking approaches, this method, with its ability to track the shape variation as well as the position changes of the ROI, is seen able to deliver greater accuracy. By adopting the Hybrid ASM approach to recover real-time shape and positional information from BEV during treatment using only one monitoring diagnostic KeV X-ray imager, we eliminated the use of marker, hence, the system less invasive compared with the current mainstream tracking approaches.

In order to further verify our approach, we are currently working on generating testing data using a pair of couple-
view DRR sequences generated from 4-Dimensional CT (4DCT) data. The results will be presented shortly.

In the immediate future, we plan to incorporate the beam geometry in the simulation environment to output a set of numerical control instructions that fits the real-world MLC system.

Although the extra dose given by the extra KeV X-ray source during treatment may be negligible, we feel it is necessary to investigate the quantity of the extra dose and its potential biological effect to the object.

In addition, automatic landmarks marking would considerably ease the work of clinical staff, therefore, it become timely in our future plan.

In order to adopt this method in a real clinical environment, a number of investigations need to be carried out, such as the potential collisions between the monitoring and treatment beam, the option of alternatively switching on each beam, also, and the accurate positioning of the sampling and treatment facilities to ensure a good alignment, which may be achieved by adaptively registering the monitoring images taken during sampling and before treatment beam switched on.

System latency may also be addressed by incorporating motion prediction algorithms such as Hidden Markov Model (HMM) into the existing tracking system.

ACKNOWLEDGEMENT

This project is funded by the European 6th Framework Programme, MAESTRO Project, Contract Number # 503564, details of the project can be found on [28].

REFERENCES:

[27] Rowland RS, 3D Volume Viewer, http://www.rmrsystems.co.uk/imaging.htm