the exhalation phase. Before the treatment delivery, the RPM block was put on patient's abdominal surface and the gating signal was generated by the RPM system. Then, the patient's position was set based on cone beam computed tomography (CBCT) compare with ITV. During the treatment, kv images were acquired at each exhalation phase of the breathing cycle and the positions of the fiducial markers were compared with their expected positions. We reported here for the five first fractions the differences between expected and real fiducial position, treatment planning parameters such as the prescription, conformity index $CI_{PTV} = (V_{ITV95\% (cc)} / V_{PTV (cc)}) * (V_{ITV95\% (cc)} / V_{iso95\% (cc)})$, homogeneity index $HI_{PTV} = (D_{2\%} - D_{98\%}) / D_{median}$ and the number of Monitor Unit (UM) per Gray. The treatment delivery parameters such as kv images acquired per fraction, the fraction's time and the room occupation's time were also mentioned.
Results: For the eight PTV patients, the average (±SD) conformity index was 0,93 ± 0,02 and homogeneity index was 0,09 ± 0,02. Average MU/Gy was 147 ± 25.

Table 1: Treatment delivery characteristics

Fractions	1	2	3	4	5
Fraction's time (min)	53	30	20	24	24
Room occupation's time (min)	59	36	26	30	30
Average kv images [range]	34 [9-56]	32 [7-60]	36 [12-56]	40 [28-74]	34 [18-48]
Average SI deviations [range] (mm)	1,00 [0-5]	0,79 [0-5]	0,81 [0-4]	1,06 [0-6]	0,91 [0-5]

Maximum deviation in the Superior-Inferior (SI) direction during the intrafraction ranged from 4 mm to 6 mm.

Conclusions: The average gating errors measured were small compare with the 5 mm margin added to the ITV to create the PTV. However, regarding to maximal error, this additional margin is suitable to treat the tumor with no misses due to the liver motion.

EP-1246
Tracking of hepatic lesions: Correlation between the movements of target and fiducials during breathing cycle
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Purpose/Objective: The liver is a mobile organ that undergoes many movements and deformations during the respiratory cycle. Nowadays, the majority of hepatic lesions treated on CyberKnife® are tracked using the Synchrony® respiratory tracking mode, using internal markers. The movements of the target are considered identical to those of the internal markers. As part of a quantification of uncertainties associated to this type of treatment, it is essential to check the correlation between the movements of target and fiducials.
Materials and Methods: The method is based on the analysis of patient data. A 4D PET-CT exam was performed for three patients treated for hepatic lesions on CyberKnife®. The exams were divided in several temporal respiratory phases, and a threshold of target detection (identical for each breathing phase) was arbitrarily determined for the segmentation, which was performed on the PET images in Oncentra MasterPlan® (*Nucletron*). The target contours were copied to the CT images. A registration, based on fiducials, was performed for each CT phase and thus of each target contour, to the primary CT phase. The similarities of target contours of each phase to the primary phase were quantified by means of indicators, such as overlap percentage and dice. The registration of contour volumes and the calculation of the different indicators were encoded in MatLab®.
Results: The method was applied to three patient data sets for which the distance between the fiducials and the lesion varies from 0.3 to 5.4 cm. The three cases studied met the recommendation for a maximum of 6 cm. Before applying our method to the patient data sets, the movements amplitude of target and fiducials between the different respiratory phases was evaluated. For the three patients, the movements of the center of mass (COM) of fiducials and target are the lowest in the x (left-right) and y (dorsoventral) direction, with a mean variation of 1 to 4 mm and a maximum variation of 2 to 8 mm. The movements in the z-direction (craniocaudal) are more important regarding mean and maximal amplitudes (up to 15 mm). The movements are globally low, but we observe that the COM of the volume of interest does not exactly follow that of the fiducials.
This observation is confirmed by the calculation of indices for comparison of different phases. Indeed, for certain phases, the coverage between two phases is better when not transforming the target contours. Note that the dice index is the best in all cases studied, when monitoring is done on the COM of the target, illustrating the correctness of MatLab ® code and providing a potential tracking method that provides better results.
Conclusions: The movements of the target seem to differ from that of the internal markers, during the respiratory cycle. In cases where the correlation between the target movements and fiducials movements is low, the possibility of using the target center of mass to improve the monitoring should be considered. The benefit of correcting the tracking by the application of a function relating the location of the target relative to the center of mass of internal markers is to be evaluated.

EP-1247
Simulating intra-fraction prostate motion using random walk and conditional Gaussian based Gibbs sampling models
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Purpose/Objective: Intra-fraction prostate movement is one of the reasons why the treated volume in radiotherapy is enlarged by adding treatment margins. Understanding the characteristics of prostate motion may allow for smaller treatment margins and adequate motion management strategies. The purpose of this study was to investigate if a model could be created that could be used for simulation of intra-fraction prostate motion.
Materials and Methods: A dataset of prostate motion traces during 548 radiotherapy fractions (mean length 607 seconds) for 17 patients was used. The motion traces were set to start at origin at the beginning of the trace and analysed to determine general patterns, average step lengths and directional frequency. We proposed four random walk models and a statistical model for simulating the prostate motion; (#1) random walk with the step lengths being the average of observed step lengths, (#2) random walk with the step lengths sampled from the distributions of observed step lengths, (#3 and #4) the same models but with simulated transient motion, and (#5) conditional Gaussian-based Gibbs sampling. The transient motion was simulated by short-lived large displacements in the superior and anterior directions. The observed traces were filtered with an averaging filter prior to being used for input to the proposed models. The number of simulated traces in each model was the same as the number of observed traces. The simulated traces were evaluated with respect to change in the average position and variance of the position over time.
Results: In the observed traces two main types of motion were identified; slow and drifting motion, mainly towards the inferior and posterior directions, and rapid and large, mainly transient, motion in the superior and anterior directions. The simulations done with random walk models #1 and #2 were unable to recreate the rapid increase of the observed variance. However, the average positions agreed reasonably. Increased agreement was achieved when transient motion was added to the models (models #3 and #4, figure 1). Using a conditional Gaussian-based Gibbs sampling, the least difference between simulated and observed traces was observed. The average error between simulated and observed traces was 0.07, 0.14, 0.12, 0.15, and 0.04 mm for model #1 through #5, respectively. The standard deviation of the difference in variance between simulated and observed traces was 0.47, 0.30, 0.25, 0.25, and 0.11 mm for model #1 through #5, respectively, showing the superiority of the Gibbs sampling model and the improved agreement with the observed variance using added transient motion in random walk models.