# New Approach for Affine Transform Parameters Estimation for Prospective Motion Correction Using External Sensors

**B. Fernandez[1,2], M. Lohezic[1,2], P-A. Vuissoz[2], and J. Felblinger[2]**

[1]General Electric Healthcare, Buc, France, [2]IADI, Inserm ERI 13, Nancy University, Nancy, France

**INTRODUCTION:** In most clinical applications, physiological information from external sensors such as ECG and respiratory belts is usually used for gating to freeze the cardiac and/or the respiratory motion during MR examination. Recently, Odille *et al.* have shown that standard physiological sensors can predict the la(rgest part of motion [1]. Other methods of real-time acquisition correction have been described [2]. Most of these methods are based on navigators [3] and predict some motion model parameters. Compared to navigators, external sensors have two advantages : they give close to continuous signals that can be used at any time and they do not disturb the MR signal since there are no extra RF pulses. We describe a new approach to drive prospective correction using external sensors, currently limited to respiratory motion. The main idea is to acquire cardiac triggered low resolution images and physiological data from external sensors. Images are used as inputs of a parametric motion estimation algorithm. The motion model is an affine transform. Finally, we compute a simple multivariate linear regression between signals from external sensors and detected motion. The linear relation is then used to predict affine transform parameters to correct a subsequent acquisition. We demonstrate that the proposed method is suitable for prospective correction of the respiratory motion.

**Materials and Methods:**

**MR Acquisition:** The validation was done on 2 healthy volunteers. For each volunteer, 10 series of 60 ECG gated images have been acquired (600 images per volunteer), each series have been acquired over 60 consecutive cardiac cycles. The first series (60 images) was used to calibrate a linear model (see below) and others were used to validate the proposed method. We acquired a single slice in short axis view in low resolution using spin echo EPI in free breathing with the following parameters : TE = 22,1 ms, SENSE acceleration factor = 2, in plane reconstructed resolution = 5,625 mm, slice thickness = 20 mm, acquisition matrix size 158x68 pixels, reconstructed matrix size = 64x64 pixels on a 1.5T scanner (Signa HDx, General Electric, Milwaukee, WI). This acquisition was repeated over time with an adaptive cardiac triggering [4] with a delay of 650 ms after the QRS. We used EPI to shorten acquisition time as much as possible; with this configuration, the acquisition time for a single slice was 15 ms which is short enough to freeze the cardiac motion. With this acquisition method, we were able to get a low resolution image per cardiac cycle. The adaptive cardiac triggering is a simplified version of the work presented in [4], meaning that the time of the next R-wave is predicted by $t_{RR}(n) = t_{RR}(n-1)$.

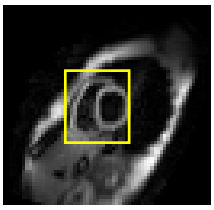

Fig. 1: Squared-shaped ROI hand-drawn over the heart on short axis image.

**External Sensors:** Two ECG and two pneumatic belts were positioned on each volunteer. Two ECG-leads were used to perform a 2D vecto-cardiography representation to obtain good information of motion. Two pneumatic belts were positioned on the thorax and the abdomen. These physiological measurements were recorded during image acquisition using home-built dedicated electronic hardware [5]. In order to reduce fast switching gradient artifacts on ECG, the algorithm presented in [5] has been used in real-time. For simplicity, we averaged signals from external sensors over the acquisition window (15ms) of each image. In this manner, we got a single measurement per external sensors for each image. We denote $S(n)$ the vector with the mean samples of each sensor acquired for the image $n$.

**Motion Estimation:** The motion model is an affine transform [6], in 2D this model requires the estimation of 6 parameters (4 parameters for rotation, scaling and shearing and 2 for translation). $P(n)$ is a vector containing the parameters of the affine transform between the $n$-th image and the reference image and $P_i(n)$ the i-th parameter. In order to estimate affine transforms between low resolution images, an algorithm based on local correlation has been implemented [7]. The reference image has been chosen manually at end-expiration and a square shaped region-of-interest including the whole heart and the diaphragm has also been drawn manually (see Fig. 1).

**Prediction:** In order to predict affine transforms parameters based on external sensors, we used a simple multivariate linear regression between $P$ and $S$: $P = \alpha S$ with $P = (P(1) \;\; P(2) \;\; \ldots \;\; P(N))$ and $S = (S(1) \;\; S(2) \;\; \ldots \;\; S(N))$. The matrix $\alpha$ can be computed by using the simple ordinary least square regression: $\alpha = P\left(S^t\left(SS^t\right)^{-1}\right)$. It is computed in a calibration step and is then used to predict the affine transform parameters based on some others physiological recordings by computing $\hat{P} = \alpha S$. Here, $P$ refers to parameters measured by the algorithm [7] and $\hat{P}$ refers to parameters estimated by our method.

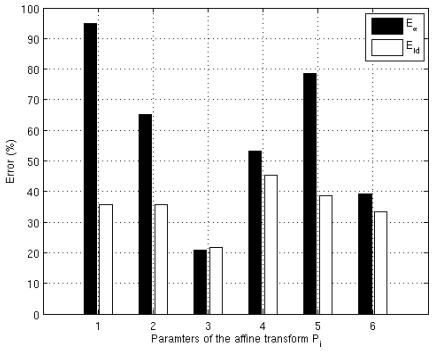


Fig. 2: RMSE (%) done on parameters $P_i(n)$ with our method (white) and if no estimation was done (black)

**Results:** To evaluate the accuracy of our method, a relative mean squared error (RMSE) was computed between parameters obtained through a motion estimation algorithm [7] and our method $E_\alpha = RMSE(\hat{P}, P)$ (see Fig.2, white plot). We compared these values with the RMSE between our method and no motion estimation $E_{Id} = RSME(Id, P)$, meaning $\hat{P} = Id$ (see Fig.2, black plot). Fig. 3 depicts mutual information within the hand-drawn ROI between the reference image and the followings images on one of the 20 series with different estimation methods. We obtained similar results on all 20 series of 60 images with a mean squared error on translation parameters between $P$ and $\hat{P}$ of 1,08 mm in x-direction (image plane) and 0.98 mm in y-direction (image plane)(standard deviations 0.47 and 0.42, respectively).

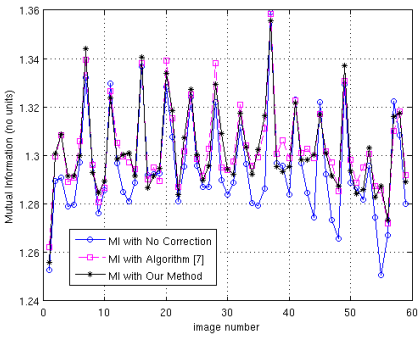


Fig. 3: Mutual information within the hand-drawn ROI between the reference image and the followings images in the same series. (blue-circle: no correction, magenta-square: corrected by algorithm [7], black-star: our method)

**Discussion:** Fig. 2 shows that our approach gives different parameter estimation compared to the motion estimation algorithm [7] but Fig. 3 shows that parameters estimation provided by our method were as accurate as the reference one in term of registration (or mutual information). This can be explained by the fact that motion parameter estimation is an ill-posed problem. Fig. 2 also demonstrates that our approach gives better results than not using image estimation correction or assuming the heart is static during acquisition. The advantage of our new method is the robustness of motion estimation: even with 15 min between the calibration image series and the last test series our method still gives good results. This mean that the calibrated model is valid for a time enabling clinical examination. Results presented here show that the use of standard external sensors for prospective motion correction is feasible. Moreover, our approach can be seen as an alternative to navigators or can be combined with them as well. In the future, we would like to extend this method into the clinical practice.

**REFERENCES:** [1] Odille *et al.* 2524 Proc. ISMRM 2007 [2] Jahnke *et al.* JMRI 2007 26:780-786 [3] Ehman *et al.* Radiology 1989; 173:255-263 [4] Oster *et al.* 2592 Proc. ISMRM 2007 [5] Odille *et al.* IEEE TBME, 54:630-640 2007 [6] Maintz *et al.* MIA Vol.2 n.1 pp 1-36 1998 [7] Netsch *et al.* Proc. ICCV pp. 501-508 2001