Linear predictive modeling of patient motion using external sensors

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INTRODUCTION
Patient motion is likely to induce mainly two kinds of problems: 1) image registration problems, in the case of rapid images which are repeated in time (e.g. in kidney perfusion studies); 2) motion artifacts (ghosting) when longer acquisition times are required (e.g. for high spatial resolution). Resulting registration problems are generally ill-posed due to important intensity variations and through plane motion. In the presence of motion artifacts, it has been shown that, if motion was known in advance, it would be possible to invert the process of artifact production and reconstruct a motion-compensated image (1). Hence both classes of problems would benefit greatly of having a predictive model of patient motion as prior knowledge. Several models have already been proposed, based on linear prediction, using navigator echo signals as inputs (2). Here we extend and validate the method to the use of external sensors measurements (3) (which are continuously available and require no dedicated pulse sequence). A new method is also proposed to determine the model coefficients, based on a variational approach.

METHODS
Acquisitions were performed on a 1.5 T MR scanner (Signa, GEHC, WI). Physiological signals were acquired using a dedicated computer and electronics system presented in (4). Two pneumatic belts are used to monitor respiration (thorax and abdomen), and two ECG sensors provide information about the cardiac phase but also about respiration through the R-wave amplitude variation. Simultaneous acquisitions of fast MR sagittal images (SSFP, 128x128 matrix, 10 fps) and of all physiological signals are performed in different respiration modes, including breathold, free breathing and deep breathing. True displacement fields are determined using the Lucas-Kanade optical flow algorithm (OpenCV, Intel). One calibration series (N images in deep breathing) is chosen for computing the coefficients $\alpha(X)$ ($X=[x\ y\ z]$, for all X in the plane/volume V) of the linear predictive model relating the true displacement fields $u(X,t)$ to the external sensors measurements $S(t)$ ($S(t)=[S_1(t),S_2(t),\ldots,S_K(t)]^T$ if K sensors are used), by minimizing the functional:

$$F(\alpha,\nabla\alpha)=\int_V\left(\sum_{t=1}^{N}\left\|S(t)\alpha(X)-u(X,t)\right\|^2\right)dX+R(\nabla\alpha). \qquad [1]$$

$R(\nabla\alpha)$ is a regularization term ($R(\nabla\alpha)=\|\nabla\alpha\|^2$ for a Tikhonov regularization for example). The solution of this variational problem is found by solving the Euler-Lagrange equation. The model is then used to predict displacement fields in subsequent imaging series, using the estimation $\hat{u}(X,t)=S(t)\alpha(X)$, with the new sensor measurement values. Validation is performed by comparing the results of prediction to the true displacement fields in subsequent image series. Regions Of Interest (ROI) were also placed on different parts of the body (diaphragm, surface of the thorax/abdomen) to perform simulations with additional sensors inputs (simulated navigator for the diaphragm), and to study the linearity between the belt signals and the true motion of the thorax/abdomen surface.

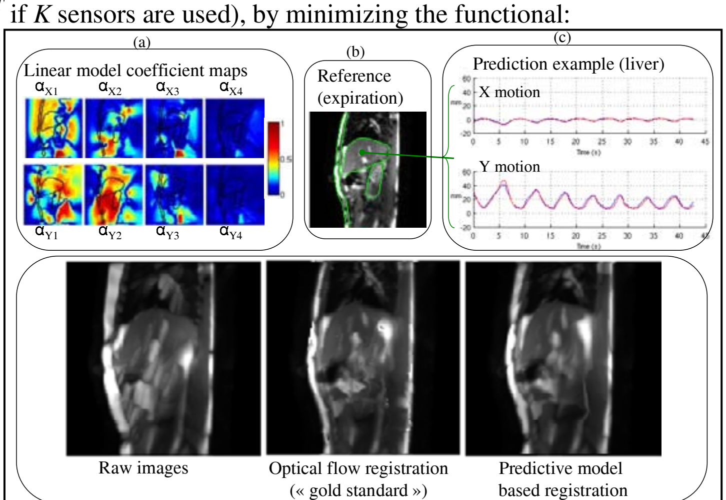

Fig.1:
(a) Maps of linear coefficients α for each sensor (1:belt-thorax; 2:belt-abdomen; 3:ECG1 amplitude; 4:ECG2 amplitude) and each direction (X, Y), determined by a calibration series (deep breathing).
(b) Reference image (some contours are drawn and reported on the α maps for anatomical marks)
(c) Example of motion prediction using the α coefficients on a subsequent acquisition (deep breathing too): the black line indicates the true motion (optical flow), the red line indicates the model prediction.
(d) Maximum Intensity Projection (MIP) view of the temporal series in which the motion prediction is performed (without/with registration)

RESULTS
Results on 6 subjects show a good linearity between the pneumatic belts and the surface ROI, even though a slight drift in time can occur. If a correction is performed to account for this drift (a linear correction was sufficient in our case), these external sensors provide good inputs for the model. An example of coefficient maps $\alpha(X)$ is given in Fig.1, as well as the results obtained with the predicted displacement fields.

CONCLUSION
The model can already provide useful prior information about the displacement fields. Further work has to be done to optimize the motion detection step, and to determine which sensors combination is the best for a given organ. It should be noted that, if navigator echo signals might be better correlated with the motion of some organs, external sensors such as belts are better correlated with the surface of the body. This is key information for the correction of respiration induced artifacts, which are generally ghosts of the image parts with the strongest discontinuities such as the thoracic surface or the abdominal fat.

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