Modeling of organ's motion using external sensors.

C. Pasquier[1,2], F. Odille[1], R. Abaecherli[1,3], P-A. Vuissoz[1], J. Felblinger[1]

[1]Université Henri Poincaré; INSERM ERI 13, NANCY, France, [2]Schiller Médical, Wissembourg, France, [3]Schiller, Baar, Switzerland

Introduction

Recent developments in MR imaging like "parallel imaging" allowed substantial improvement to the quality of images. Yet, most often used MRI sequences suffer from motion limitation, particularly respiratory-induced motion. Advanced synchronisation and real-time interaction with the MRI system (e.g. slice-tracking) permit an improvement in the quality of acquired image while reducing the respiratory artefact. However, these methods require a "best fit" of the organ's motion in order to work properly. Manke (2003) [1] have proposed prospective motion corrections based on a mathematical model using navigators as the input signal. In some cases, acquisition of both navigators and images at the same time could be a limitation to these methods. It has been suggested that external sensors may constitute a more versatile input for motion model [2]. Consequently, we propose to test the combination of several external sensors (e.g. ECG, belt) in order to investigate for the best input function that gives good correlation between external sensors and organ's motion.

Materials and Methods:

The experiment have been realised on five healthy subjects. A respiratory pneumatic belt was positioned around the subject's abdomen where the displacements are most important. Three ECG sensors (SCHILLER Médical, FRANCE) were positioned on the thorax in order to record the projection of electrical cardiac activity in the three directions of space. The sensor's signals were collected with a MagLife (SCHILLER Médical, FRANCE) custom research system. Signals were acquired with a dedicated real time computer and specific electronics (Signal Analyser and Event Controller [3]). The sampling rate of data acquisition was 1 kHz. Appropriate input for the motion estimation model as R wave amplitude and polar coordinates were extracted from signals. The image acquisition was performed with a SSFP sequence (FIESTA, TE 0,7ms, TR 2,3ms, 128x128 matrix, thickness 10mm, 156 ms/image, SIGNA Excite HD 1,5T, GE Medical System Milwaukee, WI) in the sagittal and frontal planes. A region of interest (ROI) have been manually selected around the organ of interest (e.g. right liver (Fig.1)).The motion detection was performed with a two stage algorithm; firstly a rigid preregistration by the correlation method and secondly a non-rigid registration using the Lucas-Kanade optical-flow method [3]. A displacement vector field was obtained. We used the Principal Component Analysis (PCA) to correlate the displacement's variation projections (A-P, S-I) to the extracted signals on a pixel by pixel basis. Figure 2 shows an example of the contribution map for pneumatic belt and ECG1 amplitude for A-P motion. The displacement projection variation was then fit by a model consisting of an optional combination of the extracted signals determined by the PCA. The same map could be done for all extracted signals combination.

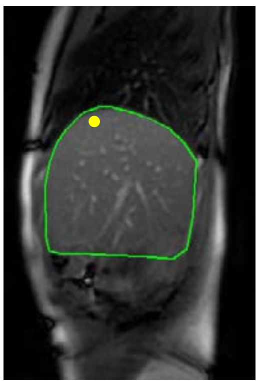

Fig 2: ROI selected for registration and selected

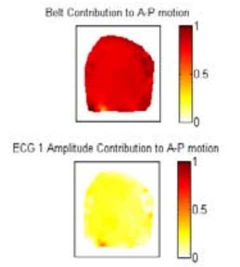

Fig 1: example of contribution Map for A-P direction

Results:

For both A-P and S-I motion we observed that some sensors have a better correlation than other sensors with calculated displacements (Fig.2). Figure 3 illustrates the sensors estimated displacement as compared to real displacement for the point indicated by the yellow disk on figure 1.

As can be noticed from the first row in figure 3, it is difficult to obtain a correct fit with one sensor only . Even when all ECG's sensors are combined (see second row in figure 3), substantial discrepancies are still visible. A better motion fit can be obtained by combination of several types of sensors (Fig.3, row 3). However we can notice a variable delay between real organ's motion and estimated displacement. Particularly for A-P direction, a better reconstructed signal is achieved if belt and extracted ECG signals are used in the input signal. The method is applied to every point or region of the ROI. We have similar result in frontal plane.

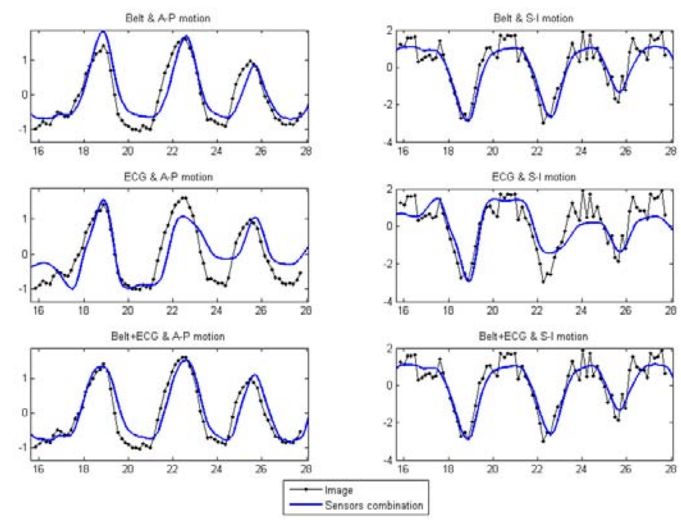

Fig 3: For a chosen point in ROI predicted displacement from indicated signal (blue) compared to real displacement (doted black)

Conclusion:

This work shows the possibility to model the organ's motion with external sensors signals. With this method it is possible to estimate the motion of an organ or part of organ at any instant in the sequence in addition. The model can be calibrated by a learning step. This enables the adaptation of motion prediction to different organs and different physiology. Investigation with other sensors and application to prospective correction like slice tracking are planned.

References:

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