AN OVERVIEW OF REGISTRATION METHODS USED FOR THE AUTOMATIC ANALYSIS OF ABDOMINAL DCE-MRI

D. Pilutti[1], C. Weidensteiner[1], M. Büchert[1], U. Fasol[1], and S. Hadjidemetriou[1]

[1]Radiology - Medical Physics, University Medical Center, Freiburg, Freiburg, Germany

Purpose:

Image registration is the process of overlaying images of the same anatomic region taken at different times. The aim of this abstract is to present an overview of recent methods used for automatic registration and analysis of Dynamic Contrast Enhanced Magnetic Resonance Images (DCE-MRI) datasets. This MRI technique implies the injection of a contrast agent which produces contrast modifications due to the wash-in/wash-out period and the type of tissue. Vital tumor tissue usually shows increased perfusion implying that the effect of the contrast agent on image contrast is more pronounced compared to healthy tissue, so DCE-MRI can be used to monitor therapy-induced perfusion changes. Current methods for dealing with biomedical datasets can address issues, which arise on the analysis of DCE-MRI for lesion quantification.

Outline of Content:

Image registration can be defined as the process of finding transformations that align two images. A Cost function is used as a metric to evaluate the registration. Some of the costs are used in DCE-MRI, such as mean square error (MSE) [2], ratio of image Uniformity (RIU) [2] and mutual information (MI) [2,6]. In the last years the evolution of DCE-MRI techniques has posed challenges to current image registration techniques which cannot sufficiently simultaneously address contrast change, motion, the limited contrast of anatomy in DCE-MRI and segmentation requirements. There can be a considerable displacement of the region of interest (ROI) due to respiration and organ movements (e.g. stomach peristalsis), a non-rigid deformation of the ROI and also a contrast variation that could lead to a misregistration and consequently an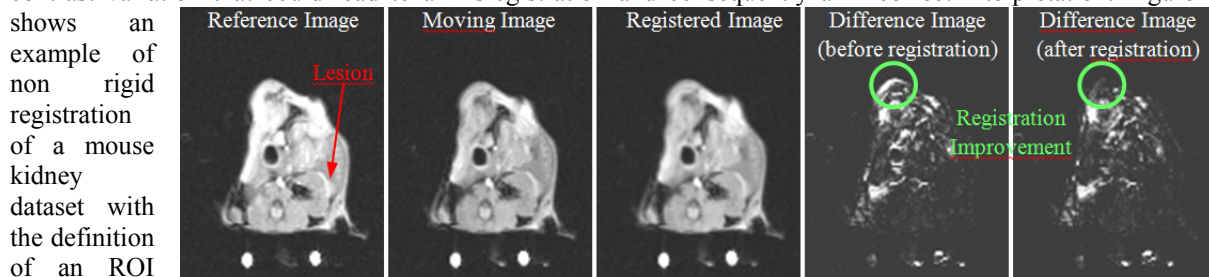 incorrect interpretation. Figure 1 shows an example of non rigid registration of a mouse kidney dataset with the definition of an ROI which includes

Figure 1: Example of non-rigid registration on mouse kidneys DCE-MRI (Dynamic range altered for visualization).

the tumor tissues. Melbourne et al. [3] proposed an approach called progressive principal component registration (PPCR) which performs a registration that can avoid the need of a physiological model and removes random motion artifacts preserving the contrast enhancement implicitly. This method is considered valid for the model-free registration of large regions of interest in DCE-MRI datasets. Gong and Brady [4] presented a registration method for breast DCE-MRI combined with segmentation. The algorithm handles global motion with affine transformations and local breast motions using free form deformations (FFD) based on B-Splines. This algorithm also segment images based on a Hidden Markov Random Measure Field (HMRMF) model using Expectation Maximization (EM). To improve the accuracy of registration Mahapatra and Sun [5] proposed a non-rigid registration method that quantifies the degree of similarity between human kidney images in pre- and post-contrast stages by using neurobiology-based saliency model along with pixel intensity information, combined with an exponential function. This method can correct elastic deformations in the presence of contrast enhancement due to wash-in of the contrast agent. To improve the performance of registration, Noterdaeme et al. [6] proposed a method that combines rigid registration to reduce extensive organ displacement and provide the result to a non-rigid registration phase which will give a more precise alignment. It is also important to consider that it is possible to simplify the computational complexity by reducing the considered area to an ROI, which also results in the reduction of the degrees of freedom that the dataset can have.

Summary:

In this abstract we presented recent methods that have benn developed for the analysis of DCE-MRI registration problem. The accuracy of the analysis is fundamental to obtain correct results; the main objective is to obtain a motion-compensated dataset with a correct time course to enable an accurate diagnosis that can lead to a proper therapy. The efficiency of the algorithms is also important to reduce the time between examination and availability of the results.

References:
[1] Zitová B., Flusser J., Image and Vision Computing 21 (2003), pp. 977-1000
[2] Periaswamy S., Farid H., IEEE Transactions on Medical Imaging, 22(7) 2003, pp. 865-874
[3] Melbourne A., Atkinson D., White M. J., Collins D, Leach M, Hawkes D, Physics in Medicine and Biology 52 (2007), pp. 5147-5156
[4] Gong Y. C., Brady M., IWDM 2008, LNCS 5116, pp. 174-180
[5] Mahapatra D, Sun Y, MICCAI 2008, Part I, LNCS 5241, pp. 771-799
[6] Noterdaeme O, Schnabel J, Brady M, MIUA 2008, pp. 256-261