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Improvement to functional Magnetic Resonance Imaging (fMRI) Methods using Non-rigid Body Image Registration Methods for Correction in the Presence of Susceptibility Artifact Effects

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Abstract-- Subject head movement, during the experimental and/or clinical procedure is an inevitable part of the functional Magnetic Resonance imaging (fMRI) brain mapping methods despite the availability of a large variety of head fixation devices employed in these studies. Thus, image registration is an essential processing step in fMRI. This is due to the fact that there is inevitable movement during the course on an fMRI experiment. An additional challenge is the explicit geometrical deformations associated with MRI. It is known that orientational changes are problematic in MRI in the presence of susceptibility differences especially between bone-tissue and air-tissue interfaces. This paper presents two registration strategies for fMRI registration, one using rigid registration based on maximization of mutual information, and the second is non-rigid registration adapted from Thirion's demons algorithm to demonstrate the importance and impact on fMRI in regions of susceptibility and its dependence on the image registration methodology.

I. INTRODUCTION

Image registration is essential to fMRI to compensate for both tranalational and rotational orientation changes produced by the patient over the course of an fMRI experiement.. An additional challenge is the well known geometrical deformations associated with susceptibility effects between different materials within the field (most commonly located near air-tissue and bone tissue interfaces [1]. While it is common that movement can be modeled for the most part as rigid body motions (ie. 6 degrees of freedom with 3 rotations and 3 translations), alteration in the local magnetic field can be strongly effected orientational differences to the main magnetic field has been documented and it has been previously shown to be a strong effect producing a resultant large number of undersirable false activations purely by orientational changes of the patient with respect to the main magnetic field [2]. As a result, we have launched an effort to evaluate the efficacy of image registration under both rigid and non rigid registration methods which can compensate partially for field effects in cases were rigid-body image registration has poorer performance. It is believed that non-rigid methodologies can to some extent improve variations in local signal variations due to magnetic resonance signal response. In light of improving computational power non-rigid body image registration techniques are becoming more rapidly feasible. The goal is of this work is to illustrate advances in non-rigid registration procedures and to determine the imply necessity of its role for fMRI particularly as such computational resources are becoming more available and more efficient.

II. ACQUISITION PARAMETERS

Functional MR examinations on healthy volunteers were performed using a circularly polarized head coil on either a 3.0 Tesla clinical imaging system (Siemens Trio, Erlangen, Germany) with 40mT/m gradient capabilities (64x64 matrix, 27 slices, field of view=220mm, slice thickness/gap = 4/1 mm, TR=2000 ms, TE=30 ms, flip angle=90^{o}) developed to exploit the BOLD contrast mechanism for the advanced analysis and/or from phantom and human volunteer data that was evaluated or on a 1.5 Tesla clinical imaging system (Siemens Vision, Erlangen, Germany). The 3T studies incorporated a Sensory-Motor design which was 4 minutes and 4 seconds in duration and was used in which two time frames were discarded to allow the signal intensity to reach steady state. The task consists of a block design with block durations of 16s on/off. During the on-block, a checkerboard stimulus appears at irregular intervals. When the checkerboard appeared, subjects were asked to press button "1" on the SRBox using their dominant hand only. Off-block was a visual fixation of a cross hair centered on the screen. For the flashing checkerboard period the interstimulus interval (ISI) ranged from 500-1000ms, with an average ISI = 762ms, (STD dev = 156ms). There were twenty-one checkerboard flashes per block and each checkerboard flash duration lasted 200ms. Fifteen total activation blocks and sixteen baseline blocks were collected (each scan had a repeat time TR=2s). The 1.5 T fMRI employed a finger tapping movement evaluation.

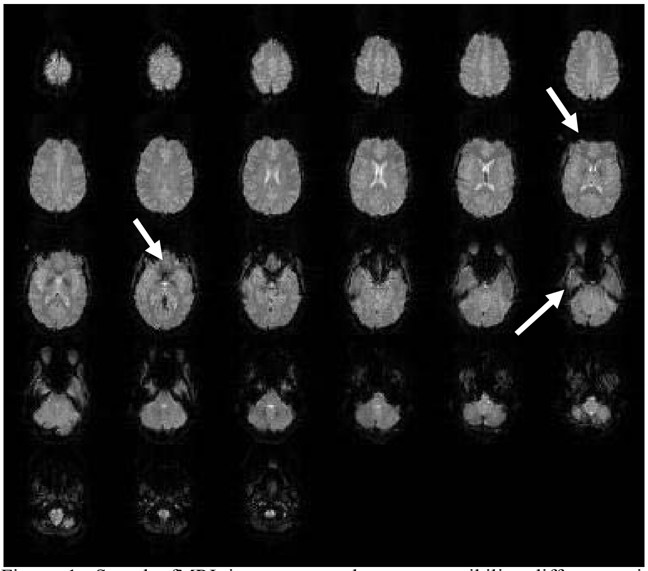

Figure 1: Sample fMRI images, note large susceptibility differences in location of the frontal, ethmoid and petrous sinuses.

III. MUTUAL INFORMATION BASED RIGID REGISTRATION

Rigid registration based on the maximization of mutual information was originally developed by Collignon et al. [1] and by Viola and Wells [2]. The simplest movement correction technique is to use rigid-body transformations inclusive of both in-plane and out-of-plane translations and rotations of the head within the image (with six or more degrees of freedom. The alignment of the images relies on the maximizing mutual information in an iterative fashion after transformation such as T:.

$$T=\begin{pmatrix} \sin\theta_x \sin\theta_y \sin\theta_z + \cos\theta_y \cos\theta_z & \cos\theta_z \sin\theta_y \sin\theta_x + \sin\theta_z \cos\theta_x & \cos\theta_y \sin\theta_x & t_x \\ -\cos\theta_z \sin\theta_x & \cos\theta_z \cos\theta_y & \sin\theta_y & t_y \\ \sin\theta_z \sin\theta_y \cos\theta_x - \sin\theta_x \cos\theta_z & -\cos\theta_z \sin\theta_x \cos\theta_y - \cos\theta_x \sin\theta_z & \cos\theta_x \cos\theta_y & t_z \\ 0 & 0 & 0 & 1 \end{pmatrix} \quad . \quad [1]$$

After registration, the spatial transformation matrix from arbitrary point $\overrightarrow{P_A}$ in A to its corresponding point $\overrightarrow{P_B}$ in B is $T_A^{-1} \times T_{opt} \times T_B$, where T_{opt} is given by:

$$T_{opt} = \underset{(\theta_x,\theta_y,\theta_z,t_x,t_y,t_z)}{\arg\max} \ MI(A,B) \qquad [2]$$

where MI is the mutual information (MI) measure such as correlation coefficient used in image registration.

Typically, images are corrected to one of the image in the series (most often can be the first image of series).During subvoxel image registration there is interpolation step which we will later relate to spatial smoothness of the data.

Initialize the displacement field for each pixel to 0.
Down sample the images to the coarsest resolution.
Repeat
  while $\nabla C > \varepsilon$ or iteration < max. iterations **do**
    Compute the force $\vec{u}$ for each pixel (Eq.1).
    Update the displacement vector (Eq.2).
    Determine deformation field and apply to model image.
    Recalculate ∇C
Increase image resolution
Until the finest resolution is reached

Table 1 Pseudocode for Demons' algorithm

IV. NON-RIGID REGISTRATION BASED ON DEMONS' ALGORITHM

Demons algorithm derives from gradient based optical flow approaches. For a given point ***P***, let *s* be the intensity in *Scene image* ***S****,* and *m* the intensity of the *Model image* ***M***. We want to deform Model image into Scene image. The estimated displacement $\vec{u}$ for arbitrary point *P* in *S* to match the corresponding point in *M* is given by [3]:

$$\vec{u} = \frac{(m-s)\nabla\vec{s}}{\nabla\vec{s}^{\,2} + (m-s)^2} \qquad [3]$$

where $\vec{u} = (u_x, u_y)$, and $\nabla\vec{s}$ is the gradient of the scene image S. $\vec{u}$ is set to zero if the denominator falls below some threshold value.

In original demons algorithm, Eq.1 is calculated iteratively. In each iteration, the optic flow computation is followed by regularization of the deformation field using a Gaussian filter. This is because the completely free-form deformation of demons may results in topological change in deformed model image. It is desirable to constrain the transformation to be smooth and thus suppress noise and preserve the geometric continuity of the deformed image. The regularization of the displacement vector is given by:

$$u_{n+1} = G_\sigma \otimes (u_n + \vec{u}) \qquad [4]$$

where G_σ is the Gaussian smoothing filter with variance *σ*, u_{n+1} is the current displacement vector for arbitrary point *P*.

Demons algorithm in this paper is implemented in a multi-resolution framework, since a multi-resolution strategy can improve registration speed, accuracy and robustness. At each resolution level, the computation of the displacement and the regularization of the displacement vector are carried out alternatively. A cost function *C* is also calculated for each iteration. The iterations continue until a given maximal number of iterations is reached or the difference of cost functions (∇C) between two successive iterations falls below some threshold value. The cost function C determines the quality of the matching between deformed model image and scene image. The iterative scheme continues until the finest iteration level is reached. The algorithm is outlined in Table. 1. In our implementation, sum of squared difference (SSD) is selected as the cost function. The threshold for each resolution level is set to *1e-5* and maximal number of iterations is *80*.

IV. EXPERIMENTAL RESULTS

The fMRI dataset used in this paper has 120 volumes, each volume with the size 64*64*27. We took first volume as reference image, and registered the other 119 volumes to the first image

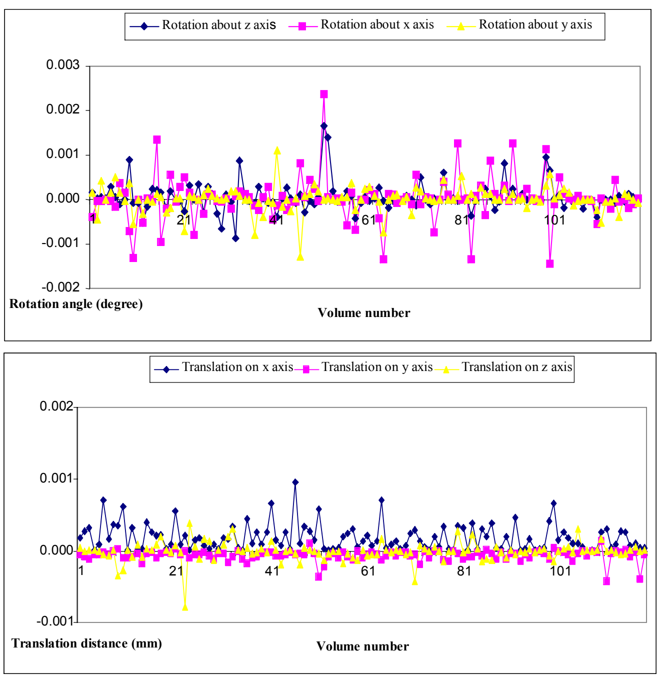

Fig.2 shows the motion parameters detected by our rigid registration algorithm.

We have presented two registration strategies applied to fMRI images. We found a consistently large improvement with non-rigid registration techniques producing an approximately average 4% of non-rigid body registration improvement over rigid registration methods (see figure 3).

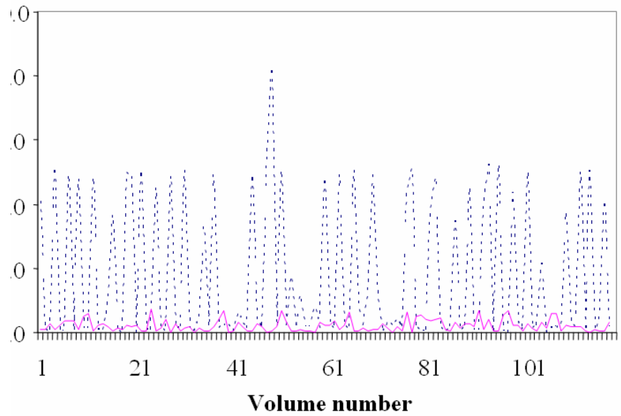

Fig.3 shows the comparison of the similarity metrics before and after registration. The results from both rigid and non-rigid registration were put into one plot. It is observed that non-rigid registration brought more promising results quantitatively, compared to rigid registration strategy. Note overall 4% average improvement over rigid registration methods is shown in this figure.

V. CONCLUSIONS

We have presented two registration strategy applied to fMRI images. In light of the overall 4% improvement in Signal variation it is believable that Such improvement is essential, as the signal produced by fMRI mechanism is estimated between 2-5% in signal. Most notable is correction near the frontal sinuses. This has strong correlation with previous reports [1]. showing greatest pronounced false activation in regions of near sinus. Such local signal variation is non-correctable by simple rigid body movement correction to complete enough extent, thus these results imply that an essential step in fMRI is to consider the use of non-rigid image registration particularly when activation is investigated in areas proximal to sinus regions.

VI. REFERENCES

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