MOTION ARTIFACT SUPPRESSION IN MRI USING REGISTRATION OF SEGMENTED ACQUISITIONS

Y. KADAH[1]

ABSTRACT

The elimination of motion artifacts in magnetic resonance imaging is a necessary part of its application in many areas. In this work, a general model for the origin of motion artifacts is developed and techniques based on the areas of signal processing, phase-space analysis and registration are utilized to solve this problem. Invariant tissue feature maps are generated from sub-band images that are acquired in small fractions of the imaging time. Subsequently, the relative motion across the different sub-bands is analyzed to assess the motion parameters of a rigid body motion model. Given the motion parameters, a gridding procedure is used to correct and re-sample the acquired k-space thus yielding artifact-free images. The theory and implementation algorithms of the new approach are presented and the effectiveness of the correction is demonstrated by several examples.
Keywords: MRI, motion artifact, image reconstruction, registration

1. INTRODUCTION

Accurate diagnosis in medical procedures has become widely attainable by the advent of the different medical imaging modalities. Among those, Magnetic Resonance Imaging (MRI) is currently one of the most promising non-invasive diagnostic tools in medicine. In addition its ability to produce anatomical images of remarkable detail and contrast, it can be used to visualize vascular structures, measure blood flow and perfusion, detect

[1] Associate Professor, Biomedical Engineering Department, Cairo University, E-mail: ymk@k-space.org

neural activation and identify the metabolic information of different areas in the acquired images. Also, its inherently volumetric acquisition allows slices at different angles to be computed easily which can be advantageous in many applications.

One of the major limitations in the present MRI technology is its susceptibility to substantial artifacts when motion occurs during the image acquisition time. Even though fast acquisition methods, such as single-shot imaging, provide a solution to this problem for some applications, these techniques are extremely sensitive to magnetic field inhomogeneity effects as compared to regular scanning methods and have a generally low signal-to-noise ratio. This makes it difficult to accurately correlate the generated images with the physical anatomy because of geometric distortion in addition to more profound signal loss within the areas of large susceptibility mismatches. Moreover, when these imaging sequences are used in such applications as functional magnetic resonance imaging (fMRI), where a set of slices are acquired repeatedly, patient motion persists in the form of low detectability of activation sites as a result of misregistration of images along the sequences.

To illustrate the origin of this problem, consider a magnetic resonance experiment in which an object of signal magnitude spatial distribution $f(\vec{x})$ is imaged. In this case, the collected data take the form,

$$F(\vec{k}) = \int_{-\infty}^{\infty} f(\vec{x}) e^{-j2\pi\vec{k}\cdot\vec{x}} d\vec{x}\,, \tag{1}$$

where $F(.)$ is the Fourier transform of $f(.)$ and k is the frequency domain parameter (conventionally termed the *k-space* in MRI). The location in k-space is a function of the history of the applied time-varying magnetic field gradient of the form:

$$\vec{k}(t) = \gamma \int_{0}^{t} g(\tau) d\tau\,. \tag{2}$$

Here γ is the gyromagnetic ratio, and $g(.)$ is the applied magnetic field gradient as a function of time. Hence, by controlling the magnetic field gradient in such a way that the k-space region of interest is covered via an arbitrary trajectory during the experiment time, an image of $f(\vec{x})$ can be reconstructed from the collected data by an inverse Fourier transformation. Due to practical constraints from the MRI machine hardware, signal-to-noise ratio and image contrast of MRI, the imaging time commonly extends to several minutes. As a result, different parts of the collected k-space are acquired at different time instants. In the ideal scenario, the imaged object does not change during the period of the experiment. The image calculated by inverse Fourier transformation is undistorted. However, in clinical MRI setups, this scenario is not usually guaranteed because of physiological and occasional voluntary patient motion and can be even impossible to realize for moving organs such as the heart and abdominal structures. Consequently, the constructed images suffer from varying degrees of distortion depending on the characteristics of the imaging sequence and the severity of motion during the scan duration. In a mathematical form, the acquired data take the form:

$$F(\vec{k}) = \int_{-\infty}^{\infty} f\left(\xi\left(\vec{x},\vec{k}\right)\right) \cdot e^{-j2\pi\vec{k}\cdot\vec{x}} d\vec{x} \,. \tag{3}$$

Here, $\xi(\vec{x},\vec{k})$ is a general function of the initial position $\vec{x}$ and time implicitly expressed in $\vec{k}$. Hence, the inverse problem here becomes the reconstruction of $f(\vec{x})$ given $F(\vec{k})$ without prior knowledge of $\xi(\vec{x},\vec{k})$, which is fundamentally different and more difficult than the original problem in (1) and severe artifacts usually result as shown in Fig. 1.

2. LITERATURE REVIEW

Several attempts to solve the problem of motion artifact in MRI have been reported in the literature. In general, the available techniques can be classified into four main categories. The first category attempts to suppress relative patient motion among different k-space lines within a given image through breath holding and chest strapping or by using cardiac and respiratory gating [1]. This minimizes the physiological component of motion between these lines at the expense of increased discomfort to the patient and/or significantly longer acquisition times. The second category uses averaging of different acquisitions to suppress the motion artifacts as well as to improve the signal-to-noise ratio of the final image. This can be done by taking the average of the corresponding k-space lines in a number of consecutive image acquisitions or more generally by composing a weighted average of the two based on optimizing a certain objective function under given constraints [1-2]. The third category applies extra magnetic gradient lobes in the imaging sequence to eliminate the effects of motion through signal refocusing assuming a simple polynomial model for this motion [3-4]. This technique is used to minimize signal loss from moving blood and Cerebrospinal Fluid (CSF) within a given voxel. Finally, the fourth category assumes simple forms of rigid body motion including translational and rotational components and corrects for them in a post-processing step. The motion in this category is estimated using navigator echo (only for translational motion) [5-6], or through automated techniques [7-9]. The effect of translational motion can be suppressed by post-processing through modifying the phase of the k-space lines according to the *a priori* knowledge about the motion [10].

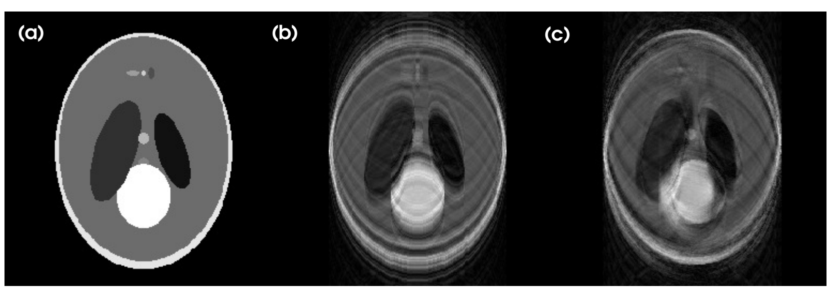

Fig. 1. Examples of motion artifacts: (a) original image, (b) motion artifact due to translational motion, and (c) motion artifact due to rotational motion.

In spite of the success that these methods have met in some applications, they represent solutions to only a restricted class of artifacts and cannot generally be applied to more complex types of motion such as deformable body motions. Moreover, the convergence properties of automatic techniques are not generally guaranteed and therefore a general lack of robustness of these methods hindered their clinical use outside research facilities.

As a result, if the patient moves significantly during the experiment, the motion artifact in the resultant images cannot be corrected. As a result, the scan has to be repeated at the expense of inefficient use of MRI machines and added discomfort to the patient. Moreover, this might not even be possible to tolerate in emergency cases. This also complicates the procedure of imaging moving organs such as the heart by adding the cardiac/respiratory gating, which again contributes to a significant prolongation of the examination time. Therefore, a technique for motion artifact suppression that does not impose any constraint on the current procedures while robustly constructing images free of motion artifact will have a rather profound impact on the current MRI technology and many of its clinical applications.

In this paper, we introduce a new approach to solve the problem of motion artifacts in MRI. In this approach, we show the possibility of estimating relative motion between the different sub-bands of the collected k-space by tracking invariant tissue signatures within each sub-band. The sub-band images are registered to estimate rigid body motion model parameters. Then, the estimated motion model parameters are used in a generalized reconstruction method to generate artifact-free images using a gridding procedure. Since each k-space sub-band is acquired within a much shorter time than the whole image, the motion artifact is substantially reduced. We present the theory, implementation and results of applying the new method. This method does not require any external monitoring or any modification to the currently available clinical imaging protocols and does not involve any iterative reconstruction. It is well-suited for direct clinical application as a post-processing step in combination with existing clinical protocols. Moreover, the new technique stimulates a new research area to develop new imaging protocols that are optimized to take full advantage of it in order to reduce imaging time, allow more freedom to the patient inside the magnet and/or allow more flexibility for intra-operative applications.

3. THEORY

3.1. Generation of Invariant Feature Maps

Consider the process of imaging a 1-D object $f(x)$ using MRI without loss of generality. Under the assumption of piecewise constant signal magnitude within individual pixels, it is mathematically possible to express any 1-D magnitude distribution in terms of a finite summation of shifted unit step functions of different amplitudes in the form:

$$f(x) = \sum_{i=1}^{N} c_i u(x - x_i) \,. \tag{4}$$

Hence, when this model is differentiated, the result corresponds to a similar summation of a number of shifted delta-functions. These delta-functions represent the edges within the image and their distribution is a characteristic feature or a *signature* of each tissue type. Each of these delta functions has a frequency domain representation that is equal to a frequency-invariant magnitude multiplied by a linear phase. Hence, windowed versions of the k-space at different locations contain similar amounts of information about those edges. In other words, given their accurate description of the underlying structures, these edges can be considered as *invariant* signatures of the tissue. That is, they can be verified from any finite-size window in the k-space.

In MRI, images/volumes are constructed by collecting their k-space representations. The motion artifacts arise from the fact that different k-space points are collected at different instances of time. The relative motion is likely to occur if the data acquisition period is long (i.e., more than a few seconds). In order to derive the tissue signature from the collected k-space data corresponding to the original image, a differentiation step must be performed. This is achieved by multiplying the k-space by a linear function in *k*, the k-space frequency variable, from the Fourier Differentiation theorem. That is,

$$f'(x) = \Im^{-1}\{jkF(k)\} = \sum_{i=1}^{N} c_i \delta(x - x_i) \,. \tag{5}$$

This is a motion-safe operation since it does not mix different points in the k-space together to derive the result. Consequently, each point in the k-space of the differentiated image maintains a unique acquisition time exactly like the original k-space.

3.2. Phase Space Decomposition

Given the nature of the data acquisition in MRI, it is reasonable to assume that the relative motion within any localized collection of k-space points is negligible. For example, if we sample an $N \times N$ k-space on a rectangular grid in a row-by-row fashion, it is possible to assume that the relative motion within any consecutive $M < N$ rows is negligible (similar examples can be applied to spiral imaging or any other general non-rectangular grid sampling with a more general form). In this case, the collected k-space is divided into a number of sub-bands, each representing a snap-shot of the imaged object within the acquisition period [7].

Several methods can be used to perform this k-space division or what we call the *phase space analysis*. As an example, consider the one-dimensional case without loss of generality. Any one dimensional signal can be divided into independent segments by windowing. That is, multiplying the signal with shifted versions of a finite width window such that the sum of all shifted windows adds up to unity everywhere within the signal support. In our application, these windows are required to be of much narrower width compared to the signal length and they are allowed to overlap. The straightforward choice of such windows corresponds to a set of non-overlapping gate functions that collectively cover the entire length of the signal. This corresponds to the example mentioned above in the case of a rectangular sampling grid. For a 1-D function *F(k)* without loss of generality, the phase-space decomposition takes the form:

$$F(k) = \sum_{i=1}^{L} F(k) \cdot \prod\left(\frac{k-k_i}{\Delta k}\right) , \qquad (6)$$

where $\prod(.)$ is the gate function, k_i is the center of sub-band i, Δk is the uniform width of the sub-bands and L is the number of sub-bands. Consequently, the sub-band images $f_i(x)$ obtained as the inverse Fourier transformations of $F_i(k)$ can be expressed as:

$$f_i(x) = f(x) * Sinc\left(\frac{\Delta k \cdot x}{2}\right) e^{j2\pi k_m x} \quad . \tag{7}$$

That is, the sum of delta-functions in (5) is converted to a sum of Sinc functions centered and peaking at exactly the same locations as the original delta-functions. An illustration of the sub-band images derived from this decomposition is shown in Fig. 2.

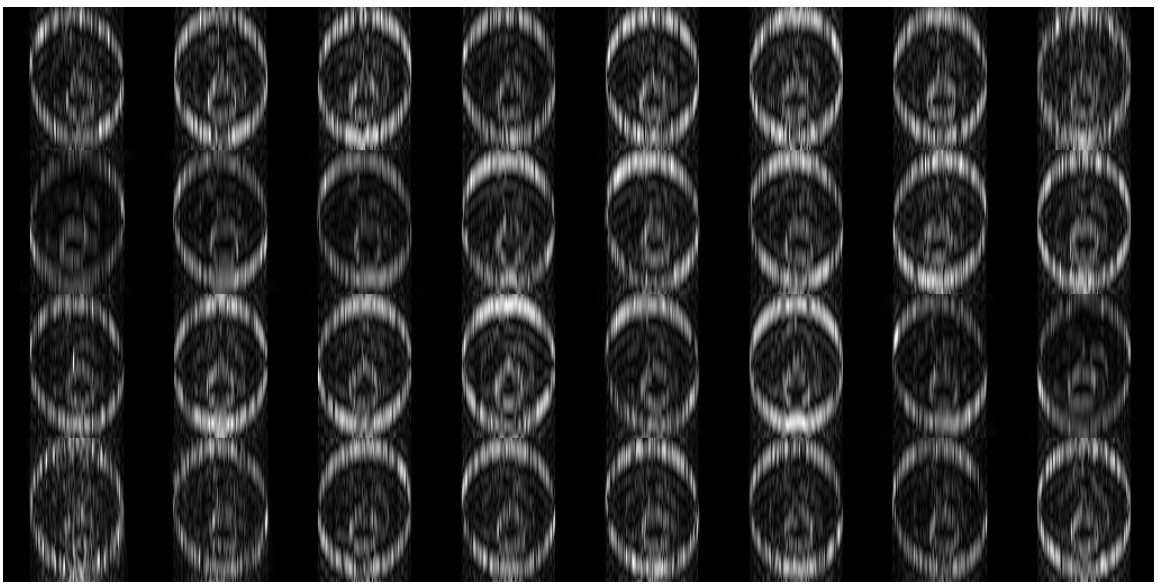

Fig. 2. Example of sub-band images exhibiting different degrees of motion.

3.3. Motion Estimation Using Sub-band Image Registration

Since moving structures tend to have well-defined boundaries, their outlines persist in the invariant feature maps. Hence, by tracking those structures, it is possible to follow and estimate the motion across different sub-band images. In particular, image registration is applied between consequent sub-band images to yield the rigid-body motion model parameters. Given the known high computational complexity associated with conventional 2D correlation-based registration techniques (since they involve whole image rotation and multiplication in every step), we present a new approach to this registration problem that enables fast and accurate implementation for practical use. Given the set of sub-band images to be registered, we start by aligning the centers of gravity of all images at the center of the image matrix as with other registration methods. Then, the registration procedure needs to compute the rotation angle around this center to fully describe the transformation matrix between the two images. Unlike previous methods that rely on rotating the whole image and optimizing a matching measure, the new method uses a different approach. A hypothetical circular perimeter around the object is considered such that its diameter is equal to the maximum of the two image dimensions (if rectangular slices are considered in the general case). The sum of all intensity values on each diameter of this circle at uniform angular steps within the range of practically realizable angles from $-\phi$ to ϕ (where ϕ is usually less than 30° under practical head coils in the MRI scanner) are computed. These values represent a projection from the two dimensional image to a one-dimensional signal given by the sum values indexed by the angle at which they were computed. Assuming that the imaged object is contained within this circle throughout the experiment and that this object does not exhibit circular symmetry, the detection of the rotational motion becomes a simple registration of two signals instead of two images in the case of in-plane patient motion. In order to avoid artifacts from partial volume effects, the diameter values to be used are computed using bilinear interpolation from their accurate floating-point coordinates. This helps eliminate this known source of bias especially for steep angles. The new technique presents a fast registration procedure with a computational complexity of $\boldsymbol{O}(L \cdot N^2)$ where L is the number of sub-band images and N is the maximum dimension of the image. The accuracy of the new method can be shown to be better than conventional methods because the partial volume artifacts resulting from having to rotate one image repeatedly to align it to another is eliminated. The developed method is illustrated in Fig. 3 where rotational motion estimation is simplified by computing diameter sum onto a circular perimeter centered at object center of gravity (left). The sum vs. angle curves are obtained and shift is used to estimate rotation by direct one-dimensional correlation (right).

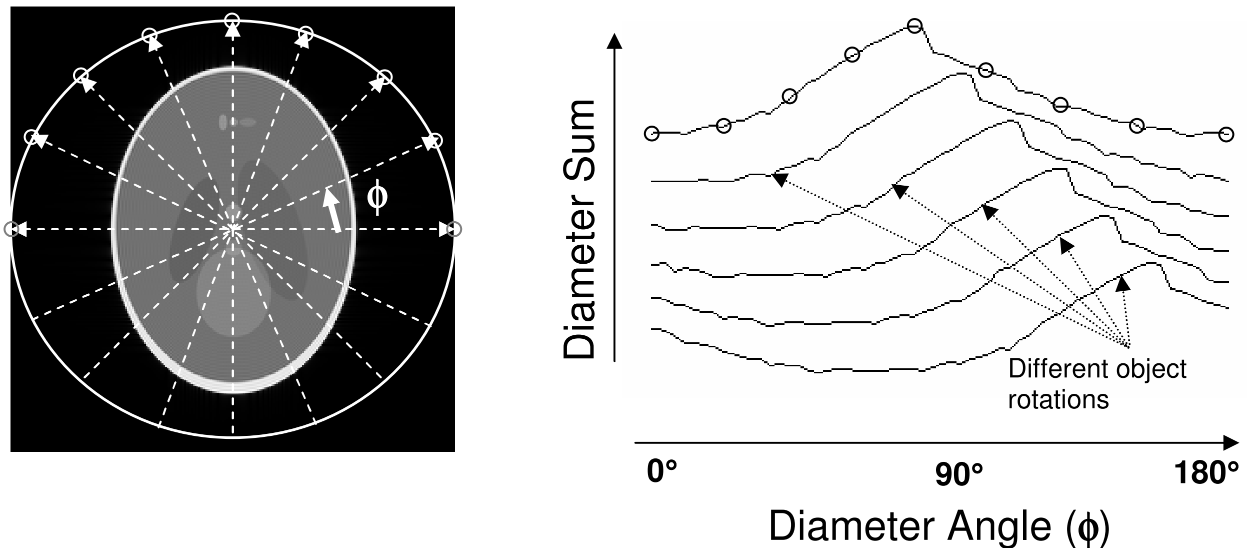

Fig. 3. Motion estimation technique based on aligning diameter sum curves.

3.4. Motion Corrected Reconstruction

With the complexity of the motion model considered in this work, the reconstruction of corrected images by motion compensation is not generally an easy problem. For example, rotational motion causes sampling non-uniformities that may be severe in some cases. Therefore, a more general form of reconstruction is used to take this problem into consideration. In particular, given the estimated motion model parameters, each k-space point in each sub-band image is associated with a certain location in the k-space of the corrected image and need not fall on a rectangular grid. Therefore, a gridding procedure similar to the one used for spiral imaging reconstruction is used to obtain a uniformly sampled k-space of the corrected image [11]. In this procedure, each point is convolved with a Kaiser-Bessel window of finite size and the results are added together and re-sampled on a rectangular grid. To compensate for the generally non-uniform sampling density, each k-space point is normalized by dividing by the amount of energy accumulated within each k-space point from different windows. Alternatively, optimal reconstruction methods based on sparse matrix solution to trade-off reconstruction speed and accuracy can be used [12-13]. Subsequently, the corrected image is computed by an inverse Fourier transformation operation. A block diagram of the proposed method is shown in Fig. 4.

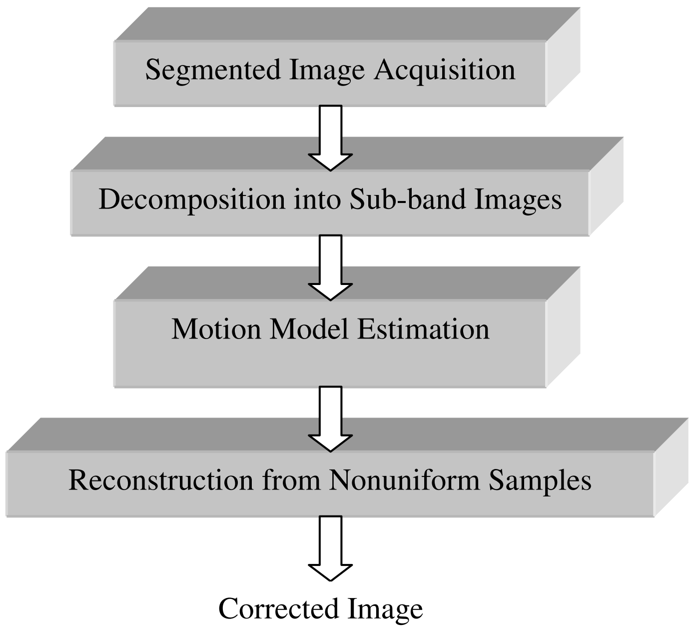

Fig. 4. Block diagram of the proposed motion estimation method.

4. EXPERIMENTAL VERIFICATION

The proposed technique was implemented to correct computer simulated motion artifacts of a Shepp-Logan phantom [14] and real human brain images that include different and random affine transformations. The motion was assumed to be negligible for each 8 or 16 consecutive rows of the 256×256 k-space, with the usual MRI convention of rows along the read-out direction and columns along the phase encoding direction. This amounts to partitioning the k-space into 32 or 16 sub-band images respectively. The distorted images were differentiated along the phase encoding direction by multiplying the k-space by jk_y prior to the decomposition into sub-band images. The different sub-band images are registered to estimate the parameters of the rigid body transformation relating each consecutive pair of sub-band images. Then, a gridding procedure was used to compute a uniformly sampled k-space, which was then used to reconstruct the corrected image by inverse Fourier transformation.

5. RESULTS AND DISCUSSION

The results of applying the new technique are shown in Figs. 5-6. In Fig. 5, examples of the estimated translation and rotation are compared to their actual values used in the computer simulation to verify the developed theory. As can be seen, the estimated values track closely the true values thus indicating the validity of the proposed model. In Fig. 6, several examples of applying the new method to correct images of different characteristics including human brain images of different contrasts are illustrated. The quality of the correction is visually evident especially near the areas indicated by the arrows. Generally speaking, the ghosting artifacts were almost completely removed and the ringing artifacts became much less prominent compared to the original images before the correction procedure.

It should be noted that the phase-space decomposition used here was chosen in such a way because of the spatial invariance of the motion model assumed. In particular, the spatial localization properties of this decomposition were not useful to exploit. However, if a more general spatially variant motion model is considered, the proposed model can be directly extended to include space/k-space localization where the motion parameters from different spatial domain windows are tracked independently and a motion map at any instant can be computed. This model can be rather useful for such applications as heart imaging where the different chambers may undergo different motions simultaneously, and in abdominal imaging where the different structures undergo different displacements with respiration.

It should be noted that the computational complexity of the proposed technique is an order of magnitude lower than the leading post-processing method in the literature [9]. Given that this reduction was obtained by taking advantage of the nature of practical segmented k-space acquisition, the performance obtained from both methods was identical. This is expected given that patient motion within each segment (~10 ms) is negligible in practice.

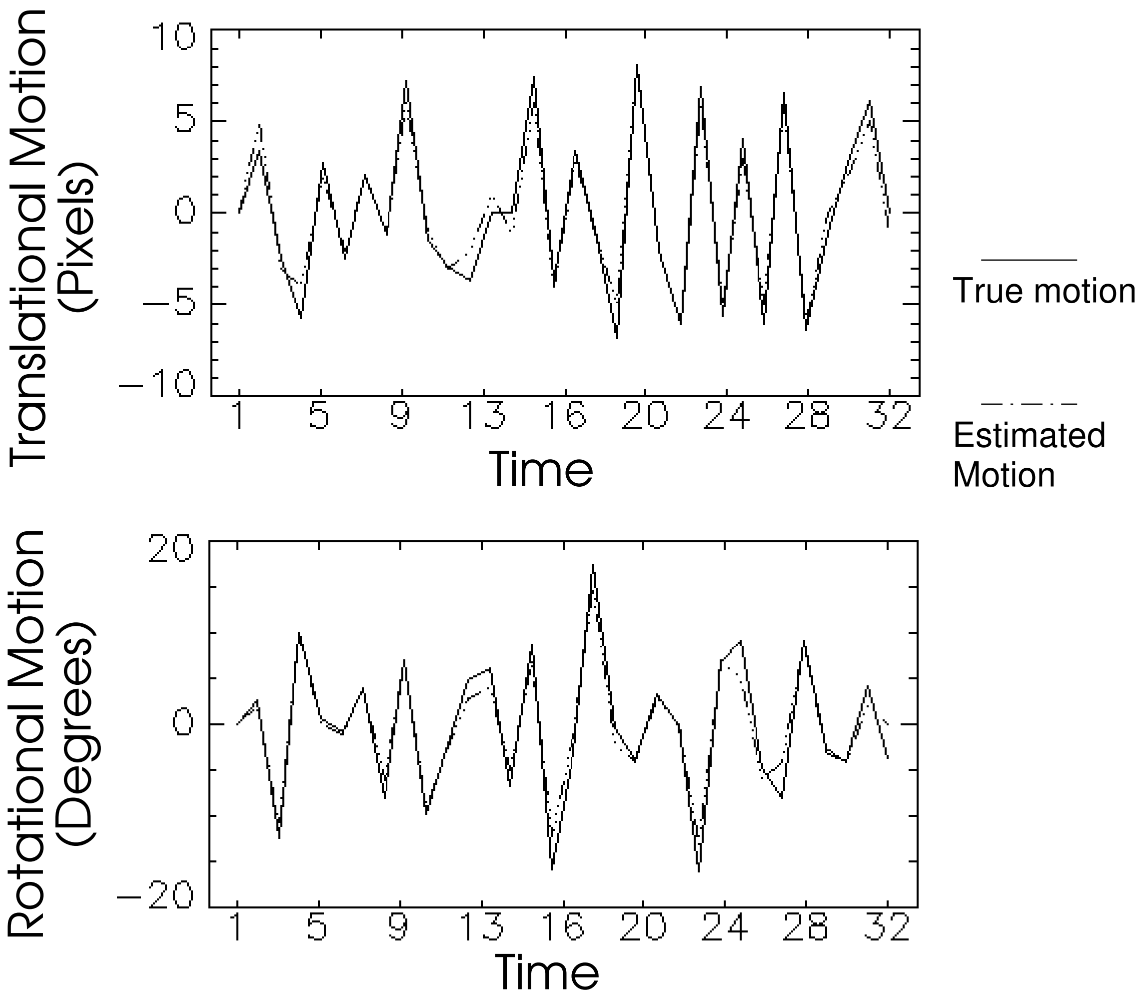

Fig. 5. Example motion estimation results comparing estimated vs. actual parameters.

6. CONCLUSIONS

The theory and implementation algorithms for a new method for motion artifact reduction in magnetic resonance imaging were developed. By tracking the motion between different sub-band images, fast estimation of the rigid-body motion during the data acquisition period can be performed without external monitoring. The estimated motion model is subsequently used in a generalized reconstruction procedure based on gridding to yield the corrected image. The results of applying the new technique support the theory and demonstrate the potential of the new technique to alleviate one of the fundamental problems in the present MRI which is motion sensitivity.

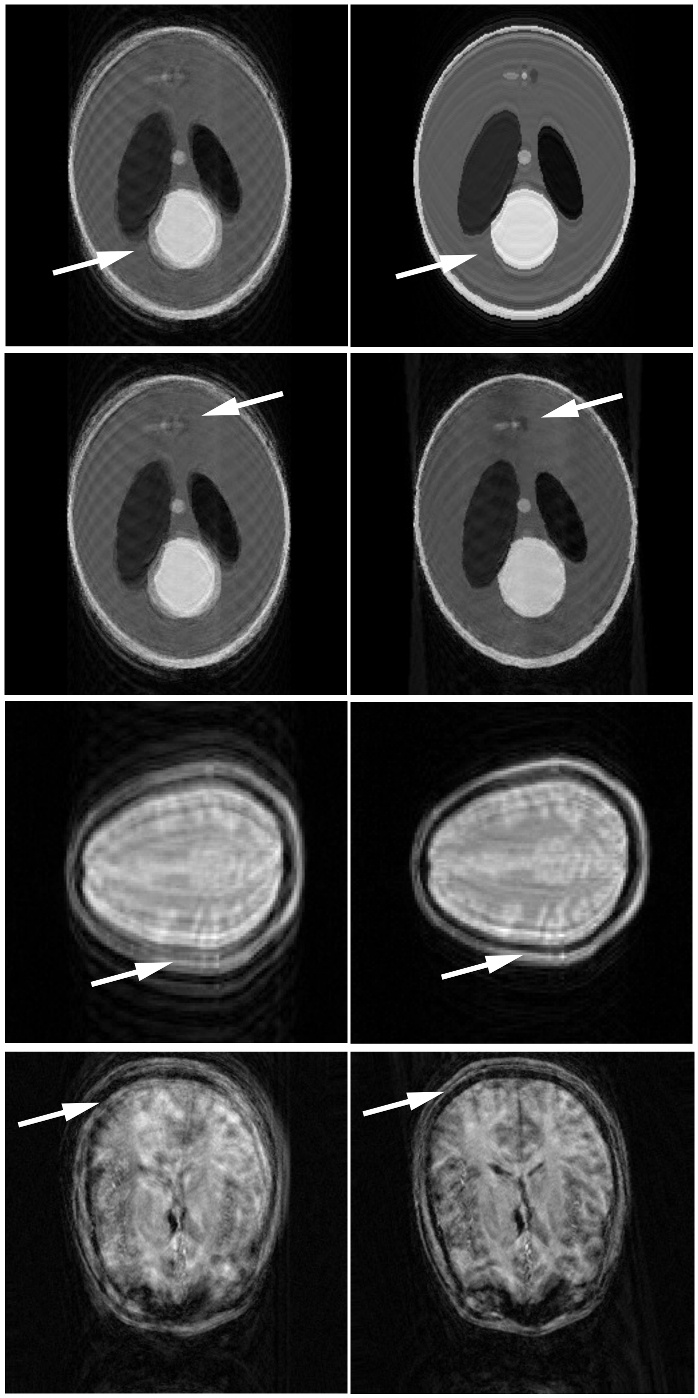

Fig. 6. The distorted images (left) and the corrected images using the new method (right).

REFERENCES

1. Wood, M.L., Henkelman, R.M., “Suppression of respiratory motion artifacts in magnetic resonance imaging,” Medical Physics, Vol. 13, pp. 794-805, 1986.
2. Madore, B., and Henkelman, R.M., “A new way of averaging with applications to MRI,” Medical Physics, Vol. 23, pp. 109-113, 1996.
3. Pattany, P.M., Phillips, J.J., Chiu, L.C., Lipcamon, J.D., Duerk, J.L., McNally, J.M., Mohapatra, S.N., “Motion artifact suppression technique (MAST) for MR imaging,” Journal of Computer Assisted Tomography, Vol. 11, pp. 369-377, 1987.
4. Haacke, E.M., and Lenz, G.W., “Improving MR image quality in the presence of motion by using rephasing gradients,” American Journal of Radiology, Vol. 148, pp. 1251-1258, 1987.
5. Ehman R.L., and Felmlee, J.P., “Adaptive technique for high-definition MR imaging of moving structures,” Radiology, Vol. 173, pp. 255-263, 1989.
6. Kadah, Y.M., Abaza, A., Fahmy, A., Youssef, A.M., Heberlein, K., Hu, X., “Floating navigator echo (FNAV) for in-plane 2D translational motion estimation,” Magnetic Resonance in Medicine, Vol. 51, pp. 403-407, Feb. 2004.
7. Kadah, Y.M., Guidry, D.L., and Farag, A.A., “Robust motion artifact reduction for magnetic resonance imaging,” Technical Report TRCVIP97, CVIP Lab, Univ. of Louisville, KY, U.S.A., 1997.
8. Felmlee, J.P., Ehman, R.L., Riederer, S.J., Korin, H.W., “Adaptive motion compensation in MR imaging without use of navigator echoes,” Radiology, Vol. 179, pp. 139-142, 1991.
9. Atkinson, D., Hill, D.L.G., Stoyle, P.N.R., Summers, P.E., Keevil, S.F., “Automatic correction of motion artifacts in magnetic resonance images using an entropy focus criterion,” IEEE Transactions on Medical Imaging, Vol. 16, pp. 903 – 910, 1997
10. Zoroofi, R.A., Sato, Y., Tamura, S., and Naito, H., “MRI artifact cancellation due to rigid motion in the imaging plane,” IEEE Transactions on Medical Imaging, Vol. 15, pp. 768-784, 1996.
11. Jackson, J.J., Meyer, C.H., Nishimura, D.G., Macovski, A., “Selection of a convolution function for Fourier inversion using gridding,” IEEE transactions on Medical Imaging, Vol. 10 pp. 473-478, 1991.
12. Kadah, Y.M., Fahmy, A., Gabr, R., Heberlein, K., Hu, X., “Progressice magnetic resonance image reconstruction based on iterative solution of a sparse linear system,” International Journal of Biomedical Imaging, Vol. 2006, pp. 1-9, 2006.
13. Gabr, R.E., Aksit, P., Bottomley, P.A., Youssef, A.M., and Kadah, Y.M., “Deconvolution-Interpolation Gridding (DING): Accurate Reconstruction for Arbitrary k-Space Trajectories,” Magnetic Resonance in Medicine, Vol. 56, pp. 1182-91, 2006.
14. Shepp, L.A., Logan, B.F., “Reconstructing interior head tissue from X-ray transmission,” IEEE Transactions on Nuclear Science, Vol. NS-21, pp. 228-236, 1974.

تقليل التشوهات الناتجة عن الحركة في التصويربالرنين المغناطيسي بتسجيل البيانات الجزئية

لكي تتم الاستفادة من صور الرنين المغناطيسي بشكل أمثل يجب ألا يتحرك المريض في أثناء التصوير حيث أن الحركة ينتج عنها تشوهات حادة تعرقل عملية التشخيص لدرجة كبيرة. هذا الشرط يضع صعوبات على المريض وعلى الجهاز وقد لايتحقق في بعض الأحيان فيستلزم اعادة التصوير مرة أخرى مما يقلل من كفاءة استخدام هذه التقنية مرتفعة الثمن و يأتي ذلك على حساب راحة المريض أيضا. في هذا البحث نقدم طريقة جديدة تتيح للجهاز تقليل التشوهات الناتجة عن الحركة بعد اتمام التصوير بدون حاجة الى اعادته. و تقوم الطريقة الجديدة على الحصول على بيانات الصورة بشكل مجزء في حيز التردد المسافي وتسجيل الأجزاء المختلفة معا بطريقة بسيطة و فعالة مما يمكن من تكوين صورة خالية من التشوهات من هذه البيانات. هذا و يقدم البحث تفاصيل الخوارزميات التي تم تطويرها للقيام بذلك و اثبات فاعلية الطريقة الجديدة بطريقة عملية على صور لنموذج رياضي و أخرى لمخ الانسان توضح التحسن الكبير في الصور بعد تطبيق الطريقة الجديدة.