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An Efficient Motion Correction Method for Frequency-Domain Images Based on Fast Robust Correlation

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Abstract

Motion artifact suppression is an important task in the medical imaging field. Motion during data acquisition can produce blurred images and artifacts. The calculation load for previous motion correction methods is relatively high. In order to decrease computational complexity, an efficient motion correction method is proposed based on fast robust correlation. Fast robust correlation is a computationally efficient search algorithm for translational image matching in the frequency domain. This method calculates the matching surface using a series of high-speed correlations by defining a kernel with sinusoidal terms. The proposed method corrects motion distorted images by aligning translational motion between images formed by neighboring frequency segments. Due to the ineffectiveness of the squared difference kernel to detect motion between partial-Fourier images, the absolute value kernel is proposed, which can be easily approximated by sinusoidal terms. Total variation of the sum of partial-Fourier images is chosen as the new match criterion. FFTs are used to calculate correlations for computational speed. Experimental results show that the proposed method can reduce image motion artifacts effectively and efficiently.

Introduction

Motion artifact suppression is an important topic in the image processing field. For medical imaging [1, 2, 3], motion during imaging is often an unavoidable issue, which may lead to a degraded image. Object motion during the signal acquisition can reduce image quality due to the induced artifacts, which further hinders diagnosis and scientific research. These degraded images may require repeated scans, which leads to treatment delay and cost increases. If the images with artifacts are not reasonably understood, erroneous diagnoses and false scientific findings may occur, which may bring disastrous consequences [4, 5].

Some sensors, such as MRI scanners and radar, acquire data in the frequency domain and then transform to the image domain using Fourier transforms. Motion may occur during the frequency-domain scan. Exhaustive search in the image domain [6] and optimization of the cost function iteratively [7] are two main methods to reconstruct motion corrupted images. However, the calculation load for both methods is relatively high. Fast robust correlation (FRC) is a computationally efficient algorithm for translational image matching in the frequency domain, first proposed by Fitch et al. [8]. This method implements a series of correlations to calculate the matching surface to increase computational speed. Robust behavior is achieved by defining a new kernel, which is composed of several sinusoidal terms. FRC is used in image registration, such as template matching [9] and image fusion [10]. Based on the sinusoidal terms kernel [8, 11], some principal component analysis methods [12, 13] have been proposed.

In this work, an efficient motion correction method based on FRC is proposed to decrease computational complexity. The proposed method reconstructs a motion-corrupted image by aligning translational motion between images formed by neighboring frequency segments. Due to the ineffectiveness of the squared difference kernel to detect motion between partial-Fourier images, the absolute value kernel is proposed, which can be easily approximated by sinusoidal terms. Total variation of the sum of partial-Fourier images is chosen as the new match criterion. Fast Fourier Transforms (FFTs) are used to calculate correlations to speed up computation.

Methods

Motion Assumption

In the proposed method, motion is assumed to be two-directional translations in a 2D plane. The whole frequency domain acquisition is assumed to have occurred over time in several non-overlapping neighboring segments, and we only consider the motion between different segments. Within each segment, the object is modeled as stationary. The motion assumption is shown in Figure 1. This assumption may not be accurate enough in some cases, but for many problems it is a good approximation.

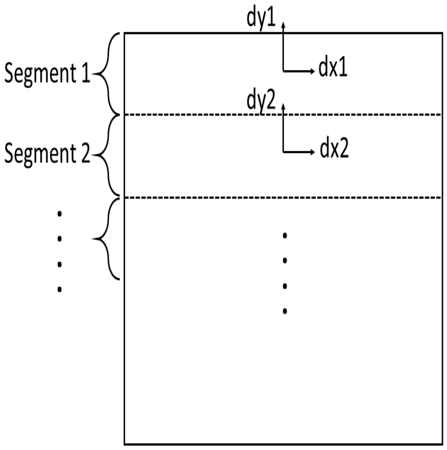


Figure 1: The whole frequency domain acquisition is divided into non-overlapping neighboring segments. Motion is only considered between segments.

Squared kernel

A matching surface is used to calculate the match quality of two images over a range of 2-D shifts. The general matching surface is expressed as:

$$S(m_x,m_y) = \sum_{x,y} h(f(x,y)-g(x-m_x,y-m_y))\alpha_f(x,y)\alpha_g(x-m_x,y-m_y), \tag{1}$$

where f and g are two images, m_x and m_y are two direction translations, (x,y) is the pixel index, and $\alpha_f(x,y)$ and $\alpha_g(x,y)$ are image masks. The squared difference kernel $h(r) = (r)^2$, where r is the pixel difference, is not suitable for motion image reconstruction in the context of non-overlapping frequency-domain segments. To see this, consider the matching surface defined in [8] as follows:

$$S(m_x,m_y) = \sum_{x,y} (f(x,y)-g(x-m_x,y-m_y))^2\alpha_f(x,y)\alpha_g(x-m_x,y-m_y). \tag{2}$$

Eq (2) can be expressed as:

$$S = (f^2\alpha_f)\otimes\alpha_g - 2(f\alpha_f)\otimes(g\alpha_g) + \alpha_f\otimes(g^2\alpha_g), \tag{3}$$

where $\otimes$ represents correlation. The first term and the third term of Eq (3) are constant and can be neglected, and the second term can be computed in the Fourier domain:

$$f\otimes g = \mathrm{ifft}(\mathrm{fft}(f)\mathrm{fft}^*(g)), \tag{4}$$

where * represents conjugate.

Since frequency segments do not overlap with one another, this term will be zero for any shifts, and the matching surface Eq (2) is constant.

Proposed match criterion

A new criterion is defined in the proposed method. The criterion is the total variation of the sum of images formed by the neighboring k-space segments. Signals with sharp edges have larger total variation in the presence of phase distortion, which is the kind of error that occurs when different frequency segments are acquired at different object positions. As part of the proposed criterion, the absolute value kernel is used:

$$h(r) = |r| \tag{5}$$

Correlation functions can be calculated efficiently with FFTs, but correlation assumes a squared kernel. In the FRC method, sinusoidal terms are used to approximate the proposed kernel, which can then be rewritten as correlations to make FFT implementation possible. A Fourier series is used to calculate the sinusoidal approximation. Since this kernel satisfies the Dirichlet conditions, the Fourier series is guaranteed to converge.

$$h(r) = |r| = a_0 + \sum_{p=1}^{\infty}(a_p\cos(pr) + b_p\sin(pr)), \tag{6}$$

The approximation becomes

$$\begin{aligned} h(r) &\approx \frac{1}{2} - \frac{4}{\pi^2}\sum_{p=1}^{P}\frac{1}{(2p-1)^2}\cos((2p-1)\pi r) \\ &= \frac{1}{2} - \sum_{p=1}^{P} B_p\cos(A_p\pi r). \end{aligned} \tag{7}$$

Figure 2 compares different number of terms p with the absolute value kernel. Based on the empirical performance, we choose $P = 3$ to approximate the absolute value kernel, which is enough to perform well in most cases.

Proposed method

f and g represent two images formed by two neighboring k-space segments. f_1 and f_2 are the first difference of f in horizontal and vertical directions. The same definition is used for g_1 and g_2. Since f_1, f_2, g_1, g_2 are all complex images, the real and imaginary parts of all these images can be represented as f_{1r}, f_{1i}, f_{2r}, f_{2i}, g_{1r}, g_{1i}, g_{2r}, g_{2i}. The matching surface is the sum of four matching surfaces, which formed by f_{1r} and g_{1r}, f_{1i} and g_{1i}, f_{2r} and g_{2r}, and f_{2i} and g_{2i}. Take f_{1r} and g_{1r} as an example to show the whole calculation process. Using Eq (7) to get the matching surface:

$$\begin{aligned} S_{1r}(m_x,m_y) &= \sum_{x,y}\alpha_{f_{1r}}(x,y)\alpha_{g_{1r}}(x-m_x,y-m_y) \\ &\times\left(\frac{1}{2} - \sum_{p=1}^{P} B_p\cos\Big(A_p\pi(f_{1r}(x,y)+g_{1r}(x-m_x,y-m_y))\Big)\right). \end{aligned} \tag{8}$$

Eq (8) is equal to:

$$S_{1r}(m_x,m_y) = \Re\Big\{\frac{1}{2}(\alpha_{f_{1r}}\otimes\alpha_{g_{1r}}) - \sum_{p=1}^{P} B_p(\alpha_{f_{1r}}e^{jA_p\pi f_{1r}}\otimes\alpha_{g_{1r}}e^{-jA_p\pi g_{1r}})\Big\}. \tag{9}$$

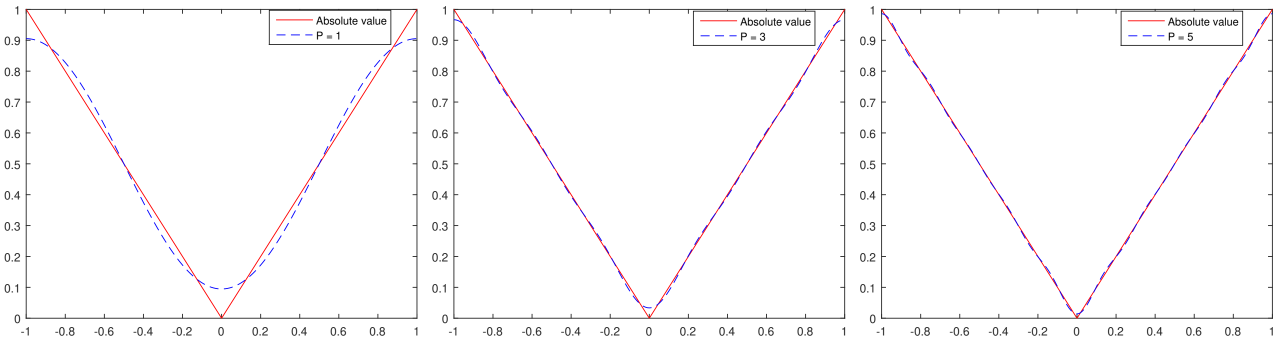
Using FFTs to Eq (9):

$$\begin{aligned} S_{1r}(m_x,m_y) = \Re\Big\{&\mathrm{ifft}\Big(\frac{1}{2}\mathrm{fft}(\alpha_{f_{1r}})\mathrm{fft}^*(\alpha_{g_{1r}}) - \\ &\sum_{p=1}^{P} B_p(\mathrm{fft}(\alpha_{f_{1r}}e^{jA_p\pi f_{1r}})\mathrm{fft}^*(\alpha_{g_{1r}}e^{-jA_p\pi g_{1r}}))\Big)\Big\}. \end{aligned} \tag{10}$$

After four matching surfaces are computed, the translations can be calculated as follows:

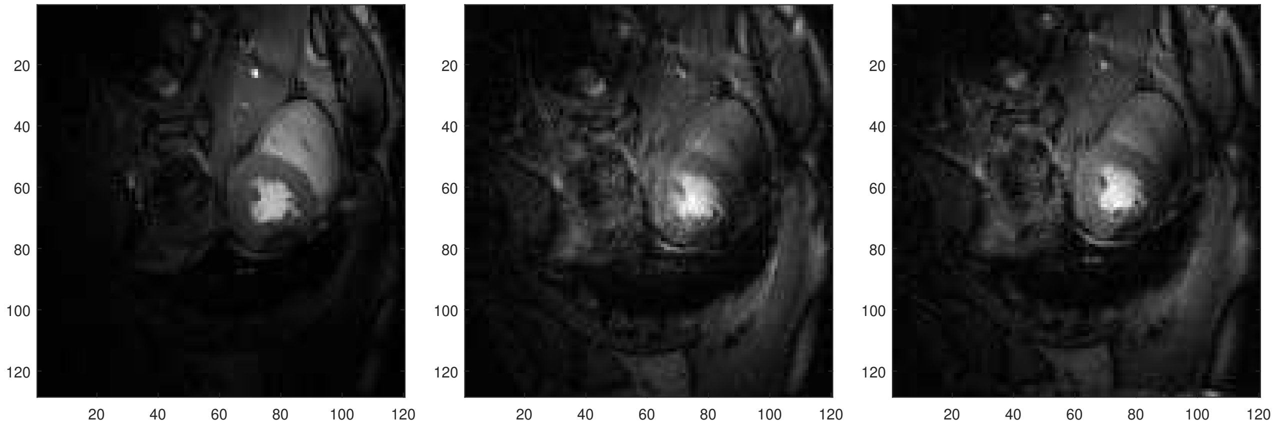
$$\begin{aligned} (\hat{m}_x,\hat{m}_y) = \underset{(m_x,m_y)}{\arg\min}(&S_{1r}(m_x,m_y) + S_{1i}(m_x,m_y) \\ &+ S_{2r}(m_x,m_y) + S_{2i}(m_x,m_y)). \end{aligned} \tag{11}$$

In order to obtain subpixel accuracy, interpolation is implemented by padding zeros in the frequency domain of the partial matching surface. After all the optimizations, all the motions between all the neighboring frequency segments relative to one reference segment are known. These motions are corrected, and the whole image is reconstructed.



(a) (b) (c)

Figure 2: Comparison different values of P and the absolute value kernel. (a) $P = 1$. (b) $P = 3$. (c) $P = 5$.



(a) (b) (c)

Figure 3: The comparison between the breath-hold no-motion image, the original free-breathing image and the reconstructed image from the original free-breathing image in one cardiac phase. (a) The breath-hold no-motion image. (b) The original free-breathing image. (c) The reconstructed image from the original free-breathing image.

Experiments

For validation of the proposed algorithm, MRI experiments were conducted. Magnetic Resonance Imaging (MRI) is a widely used medical imaging technique which exploits the phenomenon that in a magnetic field, some nuclei can absorb and then re-emit energy, which can be detected under certain conditions. MRI acquires data directly from the frequency domain, which is called k-space.

The proposed method was used to reconstruct free-breathing real MRI gating cardiac data (Auburn University MRI Research Center) in each cardiac phase. The original image was distorted due to free-breathing motion. According to the record of the ECG device, the segment size of the frequency domain was chosen as 8 frequency (k-space) lines. Figure 3 shows the comparison between the breath-hold no-motion image, the original free-breathing image, and the reconstructed image from the original free-breathing image of one cardiac phase. The breath-hold no-motion image was acquired separately as a reference image for comparison.

Discussion and Conclusion

Fig 3 shows that the reconstructed image reduces the blurs of the original image effectively, and more details are recovered in the heart region. However, there still exists some remaining artifacts, especially at the region around the heart. We think the real-world breathing motion gives rise to the remaining artifacts. Real breathing motion is not exactly a two-directional translation in a 2D plane. It includes some through-plane and non-rigid motion, which is beyond the scope of the proposed method.

The proposed method is efficient. The whole process time is around 0.8 second, so it can be used in real-time processing. Note: the proposed method is implemented in MATLAB on an 8 GB RAM Intel Core i7-3630QM 2.40 GHz CPU processor machine.

In this paper, an efficient motion image correction method based on fast robust correlation was proposed. Total variation of the sum of partial-Fourier images was chosen as the match criterion. The proposed method utilizes sinusoidal terms to approximate the absolute value kernel, which allows FFTs to be used to speed up the process. This method can be used in real-time processing.

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Author Biography

Yuan Bian received his BS in aerospace engineering and MS in information engineering from the Harbin Institute of Technology (2009 and 2011). He is a Ph.D. student in the Department of Electrical and Computer Engineering at Auburn University. His research is about digital image processing, MRI motion correction and machine learning.

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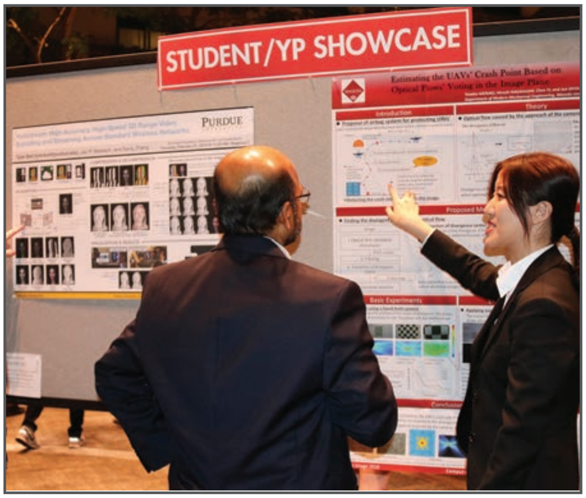
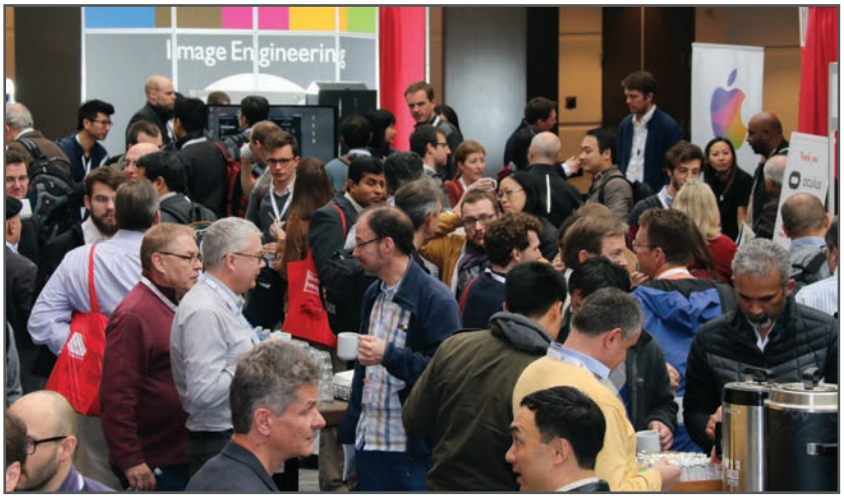
Ronald Beyers received his BS in electrical engineering from the US Air Force Academy (1984), MS in electrical engineering from the US Air Force Institute of Technology (1988) and PhD in biomedical engineering, emphasis in magnetic resonance imaging, from the University of Virginia (2010). He spent 20 years as a Development and Test Engineer for the US Air Force and the past 8 years as the Staff Magnetic Resonance Physicist at Auburn University, Alabama.



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Optimistic that it won't take another 20 to reach ubiquitous consumer AR!