GPU based fast inverse Gauss-Newton motion correction method for high throughput of MRI

Zhongnan Fang¹ and Jin Hyung Lee^{1,2}

¹Electrical Engineering, University of California, Los Angeles, Los Angeles, CA, United States, ²Department of Neurology and Neurological Sciences, Department of Bioengineering, Stanford University, Stanford, CA, United States

INTRODUCTION Motion correction across time frames is of great importance for quantitative analysis of time-series images, such as in functional magnetic resonance imaging (fMRI). Especially with the recent development of the optogenetic functional magnetic resonance imaging (ofMRI) [1-5] technology, which enables excitation/inhibition with temporal precision leading to numerous control parameters to sort through, high-speed motion correction that can be integrated into a high-throughput system is of crucial importance to accelerate scientific discovery. To enable such process, it is critical for motion correction to be conducted in real-time while leaving sufficient time for additional computationally intense processes such as iterative reconstruction and automatic segmentation to also be integrated for real-time processing. Although many fast and accurate motion correction methods have been developed so far, further improvement in speed and accuracy is necessary for efficient ofMRI studies. Here we propose a new GPU based inverse Gauss-Newton (IGN) motion correction method, which is able to reduce the traditional computation cost from O(N²) to O(N) [6]. With highly optimized computations, the IGN method performs a 128×128×23 matrix size 3D fMRI registration in approximately 5.39 ms with higher accuracy than currently available methods.



Figure 2. Accuracy test shows that the proposed parallel inverse Gauss-Newton method has higher precision compared to FSL, SPM and AFNI. The average RMS errors of 10 different 120-frame time-series with different motion parameters are shown. Our proposed parallel inverse Gauss-Newton method gives the lowest error rate for the majority of the time frames and datasets.

RESULTS AND DISCUSSION We tested the speed, accuracy and robustness of the proposed IGN method. We compared the result with currently available methods including AFNI [7], SPM [8] and FSL [9]. In the speed test, our IGN method shows the highest speed that can complete a 3D fMRI registration in 5.39 ms in average while the second fastest method, AFNI is almost 10 times slower (AFNI 51.31 ms, SPM 383.39 ms, FSL 266.76 ms). In the accuracy test, a 120-frame fMRI phantom dataset with 10 distinct sets of known motion parameters are designed. As shown in Fig. 2, our proposed IGN method shows the lowest averaged RMS error rate 0.07 mm (AFNI 0.10 mm, SPM 0.20 mm, FSL 0.26 mm). The phantom and real ofMRI data analysis results also show that the proposed IGN method gives the highest coherence value and the largest activation volume. An example is shown in Fig. 3. As demonstrated, the proposed fast IGN motion correction method (5.39 ms) combined with the 7.41 ms parallel acquisition and reconstruction method [10] leaves ample room for additional computationally intense processes to be integrated within the acquisition TR (750ms), which marks a key step forward towards the design of high-throughput ofMRI systems.



Figure 1. The proposed parallel inverse Gauss-Newton algorithm. Because the Hessian matrix (\mathbf{H}) is a constant for the inverse Gauss-Newton algorithm, the calculation is more efficient compared to the original Gauss-Newton algorithm [6], without compromising accuracy.

METHODS The proposed IGN motion correction cost function iteratively computes least square error (LSE) of two images (template T and source image I). In each iteration, a transform matrix M that registers the template to the source image is calculated through Gauss-Newton linearization. The source image is then transformed by the inverse of the M matrix. The advantage of this method is the Hessian matrix computed from the template image is fixed in all iterations and thus can be computed beforehand. This strategy dramatically reduces the computation cost from $O(N^2)$ to O(N). We implemented the IGN method on a GPU based parallel workstation (Fig. 1). Many GPU specific hardware features, such as texture caching and hard-wired interpolation, are utilized for the highest efficiency. Multi-resolution optimization strategy is also designed to increase the robustness of the algorithm.



Figure 3. Activation map before and after the parallel inverse Gauss-Newton motion correction demonstrates increased activation volume and coherence value after the proposed motion correction.

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