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Quantitative framework for prospective motion correction evaluation

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Abstract

Purpose—Establishing a framework to evaluate performances of prospective motion correction (PMC) MRI considering motion variability between MRI scans.

Method—A framework was developed to obtain quantitative comparisons between different motion correction setups, considering that varying intrinsic motion patterns between acquisitions can induce bias. Intrinsic motion was considered by replaying in a phantom experiment the recorded motion trajectories from subjects. T1-weighted MRI on five volunteers and two different marker fixations (mouth guard and nose bridge fixations) were used to test the framework. Two metrics were investigated to quantify the improvement of the image quality with PMC.

Results—Motion patterns vary between subjects as well as between repeated scans within a subject. This variability can be approximated by replaying the motion in a distinct phantom experiment and used as a covariate in models comparing motion corrections. We show that considering the intrinsic motion alters the statistical significance in comparing marker fixations. As an example, two marker fixations, a mouth guard and a nose bridge, were evaluated in terms of their effectiveness for PMC. A mouth guard achieved better PMC performance.

Conclusion—Intrinsic motion patterns can bias comparisons between PMC configurations and must be considered for robust evaluations. A framework for evaluating intrinsic motion patterns in PMC is presented.

Introduction

Head motion in brain MRI remains a major source of image degradation and artifacts. In clinics, compromised image quality due to motion can interfere with diagnostics. In research, poor image quality due to motion can reduce statistical power, introduce a bias and

could lead to misinterpretation of study outcome. Effective motion correction is therefore highly desirable for many applications in MRI.

Different approaches have been developed to various degrees of technical complexity and applicability. Among these methods, prospective motion correction (PMC), which aims to offset the impact of movements as they occur, has appeared as promising solution (1). PMC relies on monitoring the position of the volume being measured, and adjusting imaging parameters appropriately if the volume moves. This is realized by tracking movement, e.g. using an optical marker rigidly attached to a subject's head, and then updating the imaging parameters, i.e. the MRI gradient directions, RF pulses and receiver phase, accordingly. The general applicability of this concept across various MRI examinations makes this approach attractive. The robustness of PMC, however, still needs to be demonstrated as well as its clinical relevance.

A quantitative evaluation of PMC is not a straightforward task. One complication is the lack of an established procedure to comprehensively measure the detrimental effects of motion on image quality. Although various metrics have been proposed, most have been designed to characterize image blurring, focusing on the sharpness of edges (2-4). However, motion can also lead to other image artifacts including intensity anomalies such as ghosting (5).

Another difficulty in evaluating PMC in human subjects is that experimental motionless images as a "gold-standard" are practically impossible to realize and, in contrast to retrospective correction methods, the uncorrected images are not available for comparison purposes. In addition, with marker-based system, the marker fixation remains an unresolved issue because skin slippage and unrelated marker motion due to, e.g. changing facial expression, can produce erroneous updates of the position of the imaging volume and degradation of the image. Finally, relative comparisons between repeated acquisitions with and without PMC alone can be misleading since extent, timing and trajectory of movements potentially vary between scans, causing various artifacts that bias evaluations.

In this note, we address the problem of obtaining unbiased comparisons between motion corrections when a "gold-standard" without any motion is not available and variable motion between repeated acquisitions has to be taken into account. We estimated the bias that variable motion between scans can induce in motion corrections using the recordings of the in-vivo motion replayed in a separate phantom experiment, assuming a rigid body attachment of the marker to the subject's head. We assessed image quality using two different indicators: the average edge strength (2-4,6-8) and the Haralick measures of image textures (9-11), and we tested our framework to compare the efficiency of two different marker fixations: either attached on a nose bridge or mounted on a mouth guard.

Methods

This research was approved by the IRB of the University of California San Francisco and written informed consents were obtained from all subjects. The study complies with the HIPAA guidelines.

MRI protocol

Five volunteers (2M, 3F, 26±2 years old) were scanned using a 3T scanner (Skyra, Siemens Healthcare) equipped with a standard 20-channel receiver coil. A 3D T1-weighted fast spoiled gradient echo sequence (3D-MPRAGE, TR=1970ms, TE=3ms, TI=990ms, FOV=210×210×170mm³, matrix=272×272×224, 2 averages, non-selective inversion and water-selective excitation pulse, scan time=19min) was used to acquire high-resolution anatomical images of the whole brain. The subjects were asked to remain still and no additional padding was used. Accelerated acquisitions were not used. Instead, long scan time was favored to increase the likelihood of motion during imaging acquisitions, as well as to improve signal-to-noise (S/N) for improved image comparisons. The scanner was equipped with a MR compatible in-bore camera that tracked motion by recording the position of a Moiré Phase Tracking marker (Metria Innovation) (12). The camera remained mounted inside the bore throughout the study. The regular 3D-MPRAGE sequence was modified to update the imaging volume in real time based on the XPACE library (13).

The imaging protocol was repeated in all subjects for 3 different configurations in two different sessions: Session #1: PMC enabled with the marker mounted to a mouth guard (Mouth Guard) (Fig.1A). Session #2: a) PMC enabled with the marker mounted to the nose bridge (Nose Bridge) (Fig.1B), b) PMC disabled (No PMC) but motion recorded using the marker mounted to the nose bridge.

In another experiment, the same MRI protocol was employed for imaging a phantom. First, a motionless phantom image was acquired with PMC disabled as reference. Then, by modulating imaging parameters according to the in-vivo motion recordings, 'replayed' motion artifacts were induced in the phantom experiment that correspond closely – under certain assumptions, see discussion section – to the ones expected in-vivo if PMC was disabled (4) (Fig. 1DFH). To maintain consistency across these acquisitions, tuning – i.e. shimming and frequency adjustment – was done only once at the beginning of the session.

Post Processing

To reduce non-rigid motion artifacts (e.g. neck, jawbone, eyes), the analysis was performed on skull stripped brain data using the Brain Extraction Tool of FSL (14). For the phantom data, a mask extracted from the reference phantom volume was delimited and applied to all phantom data. During the continuous phantom scan session, heating of the shim elements induced a drift in the main magnetic field intensity that impacted the prescribed flip angle and yielded a drift in the MR signal intensity. This MR signal drift was corrected based on the signal equation, the RF pulse profile and a bi-exponential model for the heating processes (15) (see supporting materials for details).

The images were first blindly reviewed by three observers (one radiologist and two highly trained imagers) who visually ranked the images with integer values 1, 2 or 3 in terms of image sharpness and motion artifacts for each subject (1: poor quality, 3: high quality).

Two indicators were then used to characterize image degradations due to motion. One of the indicators that quantifies the image blurring at edges is the average edge strength (AES) (2-4). It is defined for 2D images as:

$$AES(k) = \frac{\sqrt{\sum_{i,j} E(I_{i,j}^{(k)}) \left[\left(G_x(I_{i,j}^{(k)}) \right)^2 + \left(G_y(I_{i,j}^{(k)}) \right)^2 \right]}}{\sum_{i,j} E(I_{i,j}^{(k)})} \quad (1)$$

where $I_{i,j}^{(k)}$ is the image intensity of slice k at pixel location (i, j) , G_x and G_y represent the centered gradient kernels along x and y , respectively $[-1 \ -1 \ -1; 0 \ 0 \ 0; 1 \ 1 \ 1]$ and $[-1 \ 0 \ 1; -1 \ 0 \ 1]$. $E(I_{i,j}^{(k)})$ corresponds to a binary mask of the edges extracted using Canny edge detector (16). The mean value across all the slices was considered for the analysis. When blurring increases, AES values decrease.

Although edge blurring is a prominent motion artifact (Fig.2A, black arrow), inaccurate PMC and specific motion patterns can create artificial edges that yield misleading results such as, e.g. ripples (see Fig.2B, white arrow). To further characterize the image quality, we used a Haralick texture-based indicator that captures diffuse artifacts and is not limited to edges (9). This indicator is commonly used in medical image analysis for segmentation purposes (17) or classification (11) and relies on the grey level co-occurrence matrix, C . In 3D, C is defined as:

$$C_{\Delta x, \Delta y, \Delta z}(p, q) = \sum_{(i,j,k)} \begin{cases} 1, & \text{if } Q(i, j, k) = p \text{ and } Q(i + \Delta x, j + \Delta y, k + \Delta z) = q \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

where $Q(i, j, k)$ is the quantized image intensity ($n=128$ bins) at coordinates (i, j, k) and (x, y, z) define the offset distance where co-occurrences are counted. To capture effects of motion in all directions, we computed six $C_{x, y, z}$ with offsets corresponding to the 6 closest neighbors. Then we averaged and normalized the results to obtain the co-occurrence 2D distribution $\bar{c}(p, q)$. We characterized $\bar{c}(p, q)$, using the entropy defined as:

$$CoEnt = - \sum_{p=1}^n \sum_{q=1}^n \bar{c}(p, q) \log_2(\bar{c}(p, q)) \quad (3)$$

CoEnt can be interpreted as the information content of $\bar{c}$. A homogeneous image with low contrasts produces a sparse co-occurrence matrix with little information that corresponds to low CoEnt values. Conversely, a heterogeneous image with many structures and various contrasts will produce a dense co-occurrence matrix and accordingly high CoEnt values.

For the phantom data, the same two indicators were used. For the AES, the edge mask was extracted only once from the reference phantom data and transferred to all the replayed-motion phantom acquisitions. We then computed the relative difference (AES and CoEnt in %) between the measure obtained in the phantom data with the replayed-motion and the measure obtained in the reference motionless phantom data, for every motion track, marker fixations and indicators. The larger this difference, the more damaging was the motion during the in-vivo as captured by the metric. This difference was used as a covariate variable in our statistical model to consider in the analysis the intrinsic motion of the subject.

Statistics

To obtain estimates of the performance of the difference configurations while also accounting for the inter-subject variability, we designed a linear mixed effects model with random variations of intercepts for each subject. The mixed effects analysis was done in R (R – The Project of Statistical Computing) using the lme4 package. To test whether the differences between the different marker fixations were significant, we compared the full model with the fixed effect (marker fixations) against one without the fixed effect using maximum likelihood tests and reported the results in terms of p value and $\chi^2(d)$ with d the degree of freedom. We then compared how this significance varied when adding the intrinsic motion evaluated with the same indicators as a covariate in the fixed effect (motion model). In addition, the Akaike Information Criterion corrected for finite sample sizes (AICc) of the two different models was used to compare the likelihood of the models.

Results

Representative images from subject S3, are presented in Figure 2-ABC. Qualitatively, the images obtained with the Mouth Guard and the Nose Bridge fixations (Fig.2BC) offer an overall better quality in terms of sharpness than the image acquired with No PMC (Fig.2A) (see zoom inserts). However, in this subject, ripples are observed in the occipital lobe with the Nose Bridge configuration (Fig.2B). As these ripples do not correspond to edges, the AES indicator does not capture these artifacts. However, they are presumably captured by the CoEnt indicator.

Figure 2-DEF shows samples of phantom data acquired with replayed-motion. The strong motion observed in subject S2 can be clearly discerned in Figure 2F (white arrow) and results in an important blurring artifact.

The marker motion trajectories are reported in Figure 3, columns A and B. In column A, the norm of the marker translation vector (in mm) is displayed for all 5 subjects and for the three different configurations. In column B, the same translational displacements are summarized with box plots. With the exception of subject S2, all others moved their heads in the range of ± 2 mm throughout the 20 min acquisitions. A larger motion is observed in S2 (± 6 mm) consistently across the different marker fixations, suggesting this subject exhibited larger motion behavior inside the scanner than other subjects. No obvious evidence of a difference in motion patterns due to unrelated motion, such as e.g skin slippage, is observed when comparing the Nose Bridge fixation to the Mouth Guard configurations.

The relative difference between the phantom data with the replayed-motion and the reference motionless phantom data are presented in columns C and D, for the AES and the CoEnt indicators respectively. The phantom data makes it possible to summarize the image degradation produced by the motion on the original in-vivo image as captured by the indicator. A significant difference is found between the No PMC configuration and the Mouth Guard configuration based on the AES indicator ($\chi^2(1) = 4.061$, $p = 0.044$). Difference in motion trajectories between the 2 scans of the MRI session #2 (No PMC vs Nose Bridge) were not significant, suggesting no substantial increase in subject motion, e.g. due to tiredness, after prolonged acquisition.

Figure 4 and Table 1 present the image scores obtained for the visual ranking and the two indicators. The visual ranking shows a higher image quality score with an increased reproducibility for the Mouth Guard (2.7 ± 0.2) compared to the Nose Bridge (1.9 ± 0.7) or the No PMC setups (1.6 ± 0.6). A significant improvement is found between the No PMC configuration and the Mouth Guard configuration ($\chi^2(1) = 11.5$, $p < 0.001$). To a lesser extent, a significant improvement is observed between the Mouth Guard and the Nose Bridge ($\chi^2(1) = 4.56$, $p = 0.033$).

The results obtained with the AES and CoEnt are displayed in Figure 4B and 4C. Both are in agreement with the visual ranking and the seemingly outperformance of the mouth guard. Two different statistical analyses are reported depending on whether or not the image degradation due to motion measured within the phantom data is included as a covariate in the fixed effect of the model. When the phantom data are not considered, significant differences between all configurations are found for the AES indicator: No PMC vs Nose Bridge ($\chi^2(1) = 4.0$, $p = 0.045$), No PMC vs Mouth Guard ($\chi^2(1) = 12.4$, $p < 0.001$) and Nose Bridge vs Mouth Guard ($\chi^2(1) = 6.5$, $p = 0.011$). Based on the AICc values, the motion model with the covariate intrinsic motion appears 0.1 times as probable to minimize the information loss. With this model, the significance of the difference between all configurations is slightly reduced. We obtained: No PMC vs Nose Bridge ($\chi^2(1) = 3.1$, $p = 0.078$), No PMC vs Mouth Guard ($\chi^2(1) = 10.6$, $p < 0.01$) and Nose Bridge vs Mouth Guard ($\chi^2(1) = 6.5$, $p = 0.010$). For the AES indicator, considering the intrinsic motion, the Mouth Guard configuration seems also to significantly perform better than the Nose Bridge configuration.

On the contrary, when CoEnt was used as metric, no significant difference between the Nose Bridge and the Mouth Guard configurations is found even when taking the intrinsic motion into consideration. Using CoEnt, significant differences are observed only between the No PMC vs Mouth Guard ($\chi^2(1) = 5.55$, $p = 0.018$ and $\chi^2(1) = 5.22$, $p = 0.022$ for the motion model) and between No PMC vs Nose Bridge ($\chi^2(1) = 7.91$, $p = 0.0049$ and $\chi^2(1) = 9.36$, $p = 0.0022$ for the motion model).

Discussion

We presented a framework to quantitatively evaluate PMC configurations considering intrinsic variability in the subject's motion as a covariate, and we tested this framework to compare two different marker fixations.

A major complication in quantifying image improvements from PMC is the relative comparisons between different PMC configurations because it is practically impossible to repeat the exact same motion of the human subjects across multiple acquisitions. We attempted to resolve this issue by replaying motion from in-vivo marker trajectories into phantom data. By comparing phantom images with motion-replayed to motionless phantom images, we obtained a measure of the intrinsic motion that occurs during each in vivo acquisition and used this measure as a covariate in models that compare the different PMC configurations. While this approach requires an additional scan for the phantom, it does not increase the acquisition time for the subject. To be effective, the rigid body relationship

between the marker and the subject's head must be maintained throughout the acquisition. Unrelated motions between the marker and the head, e.g. skin slippage, wrinkling, sneezing, can induce artificial motion trajectories and potentially corrupt our proposed framework. In this regard, the Nose Bridge is possibly more sensitive to unrelated motion than the Mouth Guard. However, techniques have been independently proposed that deal with the detection of these unrelated motion – e.g. see Singh et al. using multiple markers at the same time (18). These techniques have the potential to further improve the robustness of the proposed framework.

Another limitation of the framework is that the replayed acquisition may not precisely replicate the motion artifacts seen during the in-vivo scans since differences in B_1 sensitivity, B_0 inhomogeneity, spin-history or camera latencies may produce additional image artifacts. Nonetheless, motion replays have been shown effective in accurately reproducing artifacts due to arbitrary motion in phantom and in-vivo experiments (4). Alternatives to replaying motion in phantom data exist. On the acquisition side, an additional measurement with PMC disabled can be acquired for comparison with PMC enabled, either interleaved (3) or sequential (19-21). However, the scan time is double for the subjects and – perhaps more critically – the analysis is potentially skewed since the head movement patterns will likely differ between the two acquisitions. Retrospective simulation of the motion artifacts is also an option. However, the simulations are sequence dependent, computationally challenging and difficult to generalize across vendor platforms. Furthermore, the phantom used in this study may not reproduce the full range of artifacts observed in vivo. Although highly structured, it does not mimic for example the gray matter/white matter contrast which may impact the evaluation of the intrinsic motion.

The average edge strength has been used before for quantifying image degradation due to motion (2-4,6). It is efficient for characterizing the sharpness of boundaries that usually become blurred due to motion. However, motion can also generate ghost images which create additional edges and, erroneous PMC can produce ripples as seen in Figure 2B. To mitigate these effects and capture alterations away from boundaries, we explored the use of the 3D co-occurrence entropy, which is more sensitive to distributed image features. The two indicators differ in the significant differences they found between the PMC configurations. Specifically, no difference was found with the AES between the Nose Bridge and No PMC configurations whereas CoEnt detects a significant difference. This could be explained by the very specific texture observed with the Nose Bridge configuration, such as the ripples shown in Fig. 2B, which is not efficiently captured by the AES indicator. It is noteworthy that, as designed in this study, the co-occurrence matrix captures the intensity variations in the closest voxel neighborhood, making it less efficient to measure low frequency texture. Interestingly, the approach can readily be extended to further offsets and additional multi-sort co-occurrence matrices that combine intensity, gradient or anisotropy of the images (22).

Our results from 5 volunteers show that PMC significantly improves image quality, in agreement with previous reports (6-8). In addition, evidence that the Mouth Guard configuration outperforms the Nose Bridge configuration is presented. However, the small sample size of our study limits generalization of these results. Further investigations in a

large sample and with additional marker fixations are required to validate the potential advantage of using a mouth guard marker. Furthermore, our analysis was limited to high-resolution 3D- MPRAGE data. The extent to which other MRI contrasts and sequences benefit from PMC in the same extent is yet to be determined. Finally, randomization of the PMC configurations should be considered in the future to limit bias toward any technical instability, e.g. such as frequency or shim drifts when multiple configurations are evaluated sequentially over long scan periods.

In conclusion, the proposed study presents a framework that provides a means to fairly compare the performance of PMC configurations, considering the differing motion occurring during different acquisitions.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Figure 1.

A) Mouth Guard device showing the molded dental guard and the 3D printed extension where the marker is mounted. B) Moiré Phase Tracker mounted on the nose bridge (Nose Bridge).

Figure 2.

ABC) Representative images of the data acquired with the different configurations. Black arrow points to motion artifacts corresponding to blurring. White arrow points to motion artifacts corresponding to ripples. DEF) Phantom data acquired with the motion of the in-vivo scans replayed in subject S2 and S3. The white arrow points to strong motion artifacts that correspond to a translation along the x-axis during the in-vivo scan in subject S2.

Figure 3.

For each subject (rows): Column A) Translational motion of the marker as tracked by the camera for the different PMC configuration: No PMC, Nose Bridge and Mouth Guard. B) Box plot summary of the motion trajectories. C) Relative difference between the AES measure obtained in the phantom data with the replayed-motion and the measure obtained in the reference motionless phantom data. D) Same relative difference for the CoEnt indicator.

Figure 4.

Image quality statistics obtained A) with the visual ranking, B) with the average edge strength indicator and C) with the entropy of the grey level co-occurrence matrix. The significant differences are displayed either without considering for the intrinsic motion (*) or with the intrinsic motion evaluated from the phantom experiment as a covariate (#). *** : $p < 0.001$, **: $p < 0.01$, * : $p < 0.05$. Same correspondence for # statistics.

Table 1

Scores obtained for the visual ranking and the two quantitative indicators averaged across all subjects (mean $\pm$ std).

	No PMC	Nose Bridge	Mouth Guard
Visual ranking	1.6 ± 0.6	1.9 ± 0.7	2.7 ± 0.2
AES (a.u.)	66.1 ± 6.5	69.6 ± 6.4	77.3 ± 3.2
CoEnt (a.u.)	2.7 ± 0.2	2.8 ± 0.2	2.9 ± 0.1