Real time functional MRI training to decrease motion in imaging studies: Lack of significant improvement

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Functional magnetic resonance imaging (fMRI) is widely used to study brain circuitry in healthy controls and in psychiatry. A major problem of fMRI studies is motion, which affects the quality of images, is a major source of noise, and can confound data if, for example, the experimental groups move differently. Despite continual reminders to experimental subjects about keeping still, however, movement in the scanner remains a problem. The authors hypothesized that showing head movement during a scanning session may help subjects learn how to keep their head still. The authors scanned subjects and displayed in real time a plot of head movement that had three regions. The authors found, in a limited sample, that the improvements were marginal and inconsistent. Thus, they concluded that this strategy, even if likely to

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work for some people, is probably not sufficiently successful to be implemented at this time. (Bulletin of the Menninger Clinic, 80(4), 348-356)

Head motion is a major source of error in functional magnetic resonance imaging (fMRI). Despite being acknowledged as a major issue for a long time (Friston, Williams, Howard, Frackowiak, & Turner, 1996), strategies to either decrease motion during acquisition (Guimaraes et al., 1998) or to correct it computationally after images have been acquired, even by acquiring different data modalities such as electroencephalography (Wong et al., 2016), are still being developed. For example, a promising approach for correcting head motion is by optical prospective motion correction. In this method, the head is tracked with a camera, and then the radio frequency (RF) pulse sequence is altered on each repetition time (TR) to adjust for the motion in real time (Todd, Josephs, Callaghan, Lutti, & Weiskopf, 2015). A major problem for fMRI studies is that motion can correlate with the task being studied (e.g., if the task includes any behavior to be performed by the subject, which is a very common practice in fMRI studies). In those cases, the likelihood of obtaining corrupted data is increased, and it becomes very hard to separate the effects of the task that depend only on motion. Virtually all fMRI studies use a motion correction strategy that includes both removal of data with unacceptable motion and coregistration of all functional images with an anatomical reference. Assuming that the brain does not change shape because of motion, all 3-D images can be almost perfectly superposed. However, even with all images perfectly aligned, the movement that occurs during acquisition cannot be accounted for (Beall & Lowe, 2014; Cox & Hyde, 1997). Moreover, head motion disturbs the magnetic resonance equilibrium of the tissue, creating transient changes in brightness that can also corrupt the functional data. Of particular interest to us is the possibility that different experimental groups (e.g., a specific group of psychiatric patients) move in slightly different ways. This can create spurious correlations that may result in false positives being reported as differences between the groups, and the assignment of those differences to the underlying psychiatric condition. Thus, strategies to diminish movement during scanning (e.g., to add padding) are necessary.

Real-time functional magnetic resonance imaging neurofeedback (rtfMRI) (Cox, Jesmanowicz, & Hyde, 1995) is an emergent technique that shows promise as a possible treatment for several conditions (Stoeckel et al., 2014), such as chronic pain (deCharms et al., 2005), depression (Linden et al., 2012), and addiction (Hartwell et al., 2013). Briefly, brain imaging data are obtained, analyzed, and sent back to the subject in the scanner, usually as a single value, so that subjects can develop their own strategies to modulate the analyzed aspect of brain function to the desired values. We adapted this to simply show subjects a value that represents head movement in the last 2 s. Thus, we used rtfMRI to try to teach people how to be more immobile during an fMRI session by showing in real time a plot depicting their head movement.

Methods

Participants

Healthy adult participants (*N* = 7, five women) were recruited by word-of-mouth. This study was reviewed and approved by the Baylor College of Medicine Institutional Review Board, and all subjects provided informed consent. This study was part of a larger study aimed at discovering possible biomarkers for psychiatric illness (McNair Initiative for Neuroscience Discovery Menninger/Baylor or MIND-MB) in which we collect clinical, brain imaging, genetic, and microbiome data from a heterogeneous sample of psychiatric inpatients at The Menninger Clinic in Houston, Texas (Ridgewell et al., 2015; Viswanath et al., 2015).

Imaging

The sequence consisted of a T1 structural scan, a pretraining resting-state functional connectivity (RSFC) scan, a training task with real-time head movement feedback, and a posttraining RSFC scan. During the 7-min training task, the subject was shown a plot of the change in head movement as the scan progressed. The pretraining and posttraining RSFC scans were included to see if the subject was able to reduce head movements after participating in the training task. Each RSFC scan was 5 min, and no other stimulus was presented to the subject other than a plus sign to fixate on during the scan. Voxel size was 3 × 3 × 3.4 mm, echo time (TE) 2 s.

Head motion feedback

Head motion was analyzed in real time using standard imaging pipelines (SPM software). From the six head motion parameters available (three translation and three rotational) we devised a single value that was feedback to the subject in the scanner. This single value represented the change in total head motion from the last 2 s of the scan. The rotational motion parameters (units of degrees) were converted to match the same units as the translational motion parameters (millimeters) by relating them to the circumference of the cerebral cortex, where one slice of the brain is modeled as a circle with a radius of 50 mm in each rotational axis. The total head motion was calculated by adding the current six motion parameters together, and the difference in head motion was calculated by subtracting the total head motion from 2 s prior to that time. This was done to simplify the feedback. Patients were shown a plot that developed during the scanning session with the difference in head motion every 2 s. The plot was divided into three regions: green for "acceptable" amount of movement, yellow for "nearing unacceptable" amount of movement, and red for "too much movement." The subject was instructed to maintain or reduce head movements based on the movement plot, as well as to perform specific actions at specific times: scratch nose, cross and uncross legs, take a deep breath, and cough. These specific actions allowed the subject to see how much head motion normally resulted from these actions.

Data analysis

The outcome was the number of data points that would be removed from analysis in the resting state sessions before and after

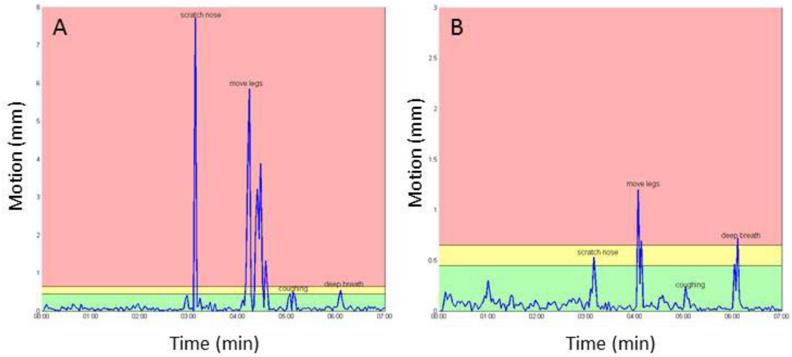

Figure 1. **Two representative plots of head motion during the real-time training session. Specific on-demand movements are labeled (scratch nose, cross and uncross legs, cough, deep breath). Subjects would see the development of this plot from no data (just the space with the three colored areas) to the end of the training session (plot as depicted). Data were updated in real time every 2 s.**

training by using different thresholds. We compared the plots from those two sessions by qualitatively assessing at the pre- and postmotion plots. In addition, we studied how many points would be rejected by the ART algorithm (Artifact Detection and Scrubbing Tool, McGovern Institute for Brain Research, Boston, MA) based on how many times the subject passed the thresholds of 2, 1, and 0.5 mm.

Results

First, as expected, we could observe peaks in head motion in real time when subjects moved "on demand." An example of the plots experienced by the subjects in the scanner is shown in Figure 1. The level of movement for the different instructions (scratch nose, cross and uncross legs, take a deep breath, cough) was not consistent between subjects. For example, in one subject "scratch nose" resulted in more movement than "move legs" while in the other subjects it was the opposite (compare panels A and B in Figure 1 for the plots of two representative subjects; note the difference in scale).

Next, we compared the motion plots for the resting state session before and after training. As seen in Figure 2 (two repre-

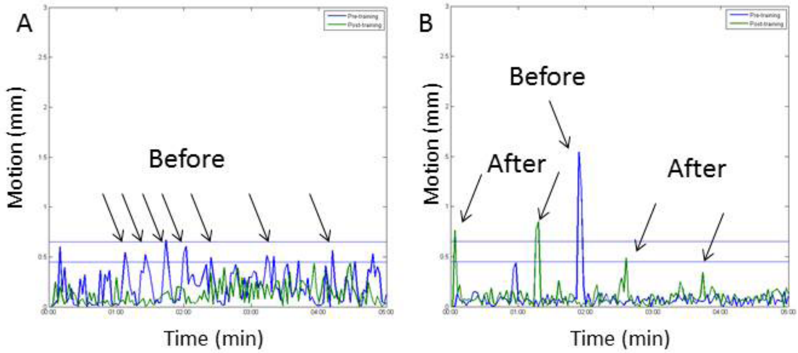

***Figure 2.* Two representative plots of head motion during the resting state sessions. Arrows show peaks of moves before and after training.**
(A) A subject who showed improvement (less motion) with training.
(B) A subject who showed more motion after training.

sentative subjects are shown) and summarized in Table 1, there is not a consistent improvement. In the seven subjects studied, we found inconsistent results, showing that training was not enough for subjects to significantly improve head motion during resting state. At the 2-mm threshold, two of the subjects had data points removed by the quality control algorithm before training, while no data point was over threshold after training. This could seem very promising, but when the threshold was changed to 1 mm and 0.5 mm, the results were very inconsistent, with some subjects showing improvement, some no change, and some showing more movement after than before training (Table 1).

Discussion

Head motion is a major problem in fMRI research studies. Strategies to diminish motion and to account for it during preprocessing are constantly being developed. We reasoned that exposing subjects to their own head motion in real time and providing feedback about the motion caused by common behaviors that happen during scanning could help subjects move less when being scanned.

Table 1. **Number of datapoints that were discarded by the ART algorithm at different motion thresholds**

Subject	2-mm Threshold		1-mm Threshold		0.5-mm Threshold	
	Pre-training	Post-training	Pre-training	Post-training	Pre-training	Post-training
1	0	0	0	0	2	0
2	0	0	0	0	0	2
3	0	0	0	0	0	0
4	0	0	0	0	4	0
5	2	0	3	5	5	8
6	2	0	4	3	32	32
7	0	0	0	2	8	5

As expected, subjects' head motion experiences spikes when they were told to perform instructed movement behaviors. Therefore, our experiment succeeded at showing subjects how their head moves during normal scanning and during those common behaviors. However, when we compared the motion parameters before and after training, no significant improvement was observed.

It is possible that other forms of real-time neurofeedback training would indeed decrease head motion. For example, it is possible that our training was simply too short to have significant effects. However, we were interested in training that could be done in a very limited amount of time because scanning time is an extremely valuable commodity (especially for patients, whose improvement is our long-term objective). Therefore, we decided to stop the trial at seven patients because results were not consistent enough to be worth the investment in patient scan time.

Some limitations must be noted beyond the obvious small sample size. First, on the 12-channel head coil we used, the head is relatively unconstrained compared to a 32-channel head coil. Training may be less variable in a channel coil that restricts movement in some directions more than others. Second, we think that the timing of the motions during training may be critical. If some movements were made fast and between TRs (i.e., rapid jerks), then the motion captured would have been reduced compared to a prolonged motion that spanned several TRs. Thus, the study could perhaps be improved by syncing the motion onsets with TR onsets and fixing the duration of the on-demand motions. Third, one could create sequences that are more optimal for motion detection. For example, faster TR, fewer slices, and increased voxel size might help to get better motion data. However, we wanted to use the same sequence we use in the parent project in which we scan psychiatric patients.

In conclusion, although we believe that it is possible that real-time head motion training may be able to decrease movement in fMRI studies, in our experience the gains are not large enough to warrant further study or implementation, at least of this specific approach.

References

Beall, E. B., & Lowe, M. J. (2014). SimPACE: Generating simulated motion corrupted BOLD data with synthetic-navigated acquisition for the development and evaluation of SLOMOCO: A new, highly effective slicewise motion correction. *NeuroImage, 101*, 21–34. doi:10.1016/j.neuroimage.2014.06.038

Cox, R. W., & Hyde, J. S. (1997). Software tools for analysis and visualization of fMRI data. *NMR in Biomedicine, 10*(4–5), 171–178.

Cox, R.W., Jesmanowicz, A., & Hyde, J. S. (1995). Real-time functional magnetic resonance imaging. *Magnetic Resonance in Medicine, 33*(2), 230–236.

deCharms, R. C., Maeda, F., Glover, G. H., Ludlow, D., Pauly, J. M., Soneji, D., . . . Mackey, S. C. (2005). Control over brain activation and pain learned by using real-time functional MRI. *Proceedings of the National Academy of Sciences of the United States of America, 102*(51), 18626–18631. doi:10.1073/pnas.0505210102

Friston, K. J., Williams, S., Howard, R., Frackowiak, R. S., & Turner, R. (1996). Movement-related effects in fMRI time-series. *Magnetic Resonance in Medicine, 35*(3), 346–355.

Guimaraes, A. R., Melcher, J. R., Talavage, T. M., Baker, J. R., Ledden, P., Rosen, B. R., . . . Weisskoff, R. M. (1998). Imaging subcortical auditory activity in humans. *Human Brain Mapping, 6*(1), 33–41.

Hartwell, K. J., Prisciandaro, J. J., Borckardt, J., Li, X., George, M. S., & Brady, K. T. (2013). Real-time fMRI in the treatment of nicotine dependence: A conceptual review and pilot studies. *Psychology of Addictive Behaviors, 27*(2), 501–509. doi:10.1037/a0028215

Linden, D. E., Habes, I., Johnston, S. J., Linden, S., Tatineni, R., Subramanian, L., . . . Goebel, R. (2012). Real-time self-regulation of emotion networks in patients with depression. *PloS One, 7*(6), e38115. doi:10.1371/journal.pone.0038115

Ridgewell, C., Bray, A., Curtis, K., Velasquez, K., Baldwin, P. R., Fowler, J. C., . . . Salas, R. (2015). Enhanced olfactory cortex connectivity in a patient with PTSD with olfactory hallucinations. *Journal of Neuropsychiatry and Clinical Neurosciences, 27*(1–2), e170–e171. doi:10.1176/appi.neuropsych.14070156

Stoeckel, L. E., Garrison, K. A., Ghosh, S., Wighton, P., Hanlon, C. A., Gilman, J. M., . . . Evins, A. E. (2014). Optimizing real time fMRI neurofeedback for therapeutic discovery and development. *NeuroImage Clinical, 5*, 245–255. doi:10.1016/j.nicl.2014.07.002

Todd, N., Josephs, O., Callaghan, M. F., Lutti, A., & Weiskopf, N. (2015). Prospective motion correction of 3D echo-planar imaging data for functional MRI using optical tracking. *NeuroImage, 113*, 1–12 doi:10.1016/j.neuroimage.2015.03.013

Viswanath, H., Velasquez, K. M., Savjani, R., Molfese, D. L., Curtis, K., Molfese, P. J., . . . Salas, R. (2015). Interhemispheric insular and inferior frontal connectivity are associated with substance abuse in a psychiatric population. *Neuropharmacology, 92C*, 63–68. doi:10.1016/j.neuropharm.2014.12.030.

Wong, C. K., Zotev, V., Misaki, M., Phillips, R., Luo, Q., & Bodurka, J. (2016). Automatic EEG-assisted retrospective motion correction for fMRI (aE-REMCOR). *NeuroImage, 129*, 133–147. doi:10.1016/j.neuroimage.2016.01.042