Automatic identification of motion in mulitshot MRI using convolutional neural networks

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TARGET AUDIENCE: The aim of this work will benefit researchers and clinicians whose investigations require automated identification of motion-corrupted data.

PURPOSE: MRI data acquired with multishot sequences are desirable for many applications, as they provide improved spatial resolution over single-shot acquisitions. However, a major concern of multishot acquisitions is the effect of subject motion between shots. Such motion produces image artifacts after reconstruction, rendering the images useless. These corrupted images can either be discarded, or corrected using a post-processing motion correction technique[1]. In either case, manually determining which images have been corrupted by motion can be a time-consuming process given large datasets, and therefore an automated approach for identifying motion-corrupted multishot data is ideal. With this aim, we present a machine-learning approach using unsupervised feature learning and convolutional neural networks (CNNs) to automatically identify motion-corrupted multishot data, thereby enabling a fast and reliable means for discarding or correcting selected multishot MRI images corrupted by motion.

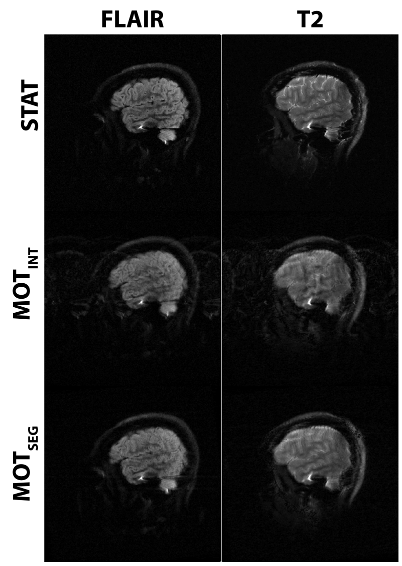

Figure 1: Three types of images to be classified for FLAIR and T2 contrast

METHODS: Stationary (without motion corruption) T2-weighted images and FLAIR images were acquired on a 3T system (GE HD, Waukesha, WI) using a 4-shot interleaved EPI sequence with a 32-channel head coil. Motion corruption was then simulated using the stationary datasets. Two types of multishot motion were simulated: 1) motion in a 4-shot interleaved sequence, and 2) motion in a 4-shot segmented sequence. This was done by applying small random spatial transformations (rotation + translation) four times to each acquired image. These four spatially transformed images were then transformed to the k-space domain, and combined in either a 4-shot interleaved fashion, or a 4-shot segmented fashion. We furthermore retained some stationary images such that the final datasets contained stationary images, images with interleaved motion artifacts, and images with segmented motion artifacts in equal proportions. We labeled these images as STAT, MOT_{INT}, and MOT_{SEG}, respectively. Examples of these image types for both FLAIR and T2-weighting are shown in Figure 1. The FLAIR dataset contained a total of 1845 images, and the T2-weighted dataset contained a total of 108 images. A CNN was trained to classify the images in our datasets as either STAT, MOT_{INT}, or MOT_{SEG}, in the following manner. First, the FLAIR dataset was split into a training set containing 1292 images, and a test set containing 553 images. The T2-weighted dataset was used only for testing, and was not included in training. Next, random 16x16 image patches from the training set were supplied to a sparse autoencoder in order to learn 16x16 feature filters[2]. Thereafter, these features were convolved and mean-pooled[3] with all 1292 images in the training set. The resulting convolved and pooled training features were used with their corresponding training labels to train a softmax regression classifier. Finally, both the FLAIR and T2-weighted test set images were applied to this trained CNN / softmax classifier, and the results were compared to the test set labels in order to evaluate the effectiveness of our machine learning framework in classifying among stationary and motion-corrupted multishot images. A diagram of our network is shown in Figure 2. Processing was performed in Matlab (The MathWorks, Natick MA) on a Linux machine (2.30 GHz CPU, 16 GB RAM).

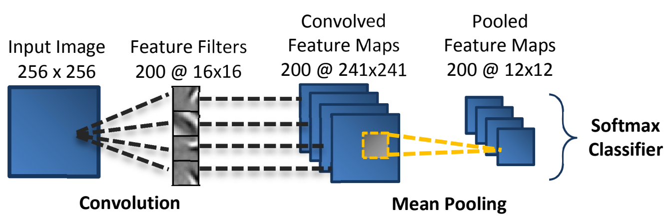

Figure 2: Diagram of CNN architecture for our classification task

RESULTS: Total training time was approximately 70 minutes. Subsequent classification time on the test set images was approximately 1.6 seconds per image. The CNN achieved an accuracy of 100% on the FLAIR test set (553/553 images correctly classified), and an accuracy of 99.07% on the T2-weighted test set (107/108 images correctly classified).

DISCUSSION AND CONCLUSION: By using an initial unsupervised learning framework to extract important features from MRI images, it was possible to subsequently use these features in a CNN to classify motion for both multishot interleaved and segmented acquisitions. An asset of the approach is that its performance is not largely affected by underlying image contrast, as the CNN was trained on FLAIR data but performed well on T2-weighted data as well. Furthermore, once the CNN had been trained, its speed of classification (1.6 seconds per image, including convolution and pooling steps) enables practical automatic identification of motion-corrupted images. In clinical/research investigations, these identified motion-corrupted images could then either be rejected or sent to a correction pipeline without the need for manual examination of the data. Consequently, we expect that this approach would be valuable for investigations in which vast amounts of multishot data must be analyzed without the deleterious effects of motion.

REFERENCES: [1] Batchelor PG, et al. Magnetic Resonance in Medicine, 54:1273-1280 (2005), [2] Olshausen BA, Field DJ. Nature, 381:607-609 (1996), [3] Krizhevsky A, Sutskever I, Hinton GE. Advances in Neural Information Processing Systems 25 (NIPS 2012)