Automated Motion Artifact Detection on Pediatric Diffusion MRI Using a Convolutional Neural Network

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BACKGROUND

Diffusion MRI (dMRI) is an imaging technique that exploits the diffusion of water molecules to generate contrast in MR images. In pediatric brains, dMRI provides information relevant for brain development such as white matter microstructure. However, it is challenging for these populations to remain still, and motion artifacts can be present. Removing images with artifacts is a manual process, which is prone to subjective error and time-consuming due to the many imaging volumes acquired. In recent years, deep learning (DL) methods have shown great success with quality control (QC) tasks, such as classifying an image as artifactual or normal. In this work, we propose a three-dimensional convolutional neural network (3D-CNN) capable of recognizing motion artifacts in dMRI images of 1- and 24-month subjects.

METHODS

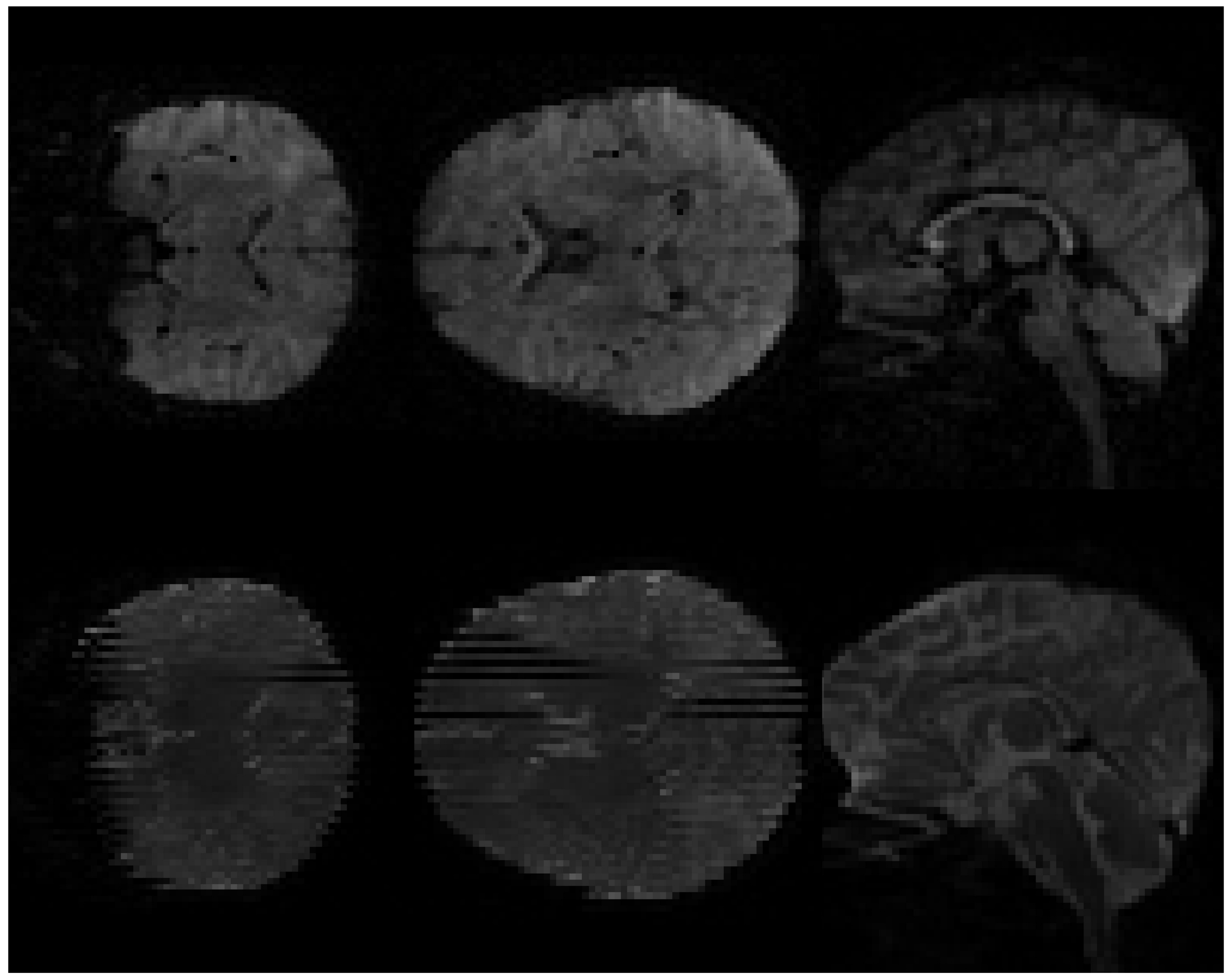
Raw dMRI images were obtained from a prior study where subjects were imaged at 1-month (n=95) and 24-months (n=24) of age. Manual QC of the subjects' 4D image volumes were performed by trained lab members and 3D sub-volumes were flagged for motion artifacts. Image volumes were zero-padded or cropped to be of size 128x128x70, and pixel intensities were normalized between 0 and 1. A 50/50 class balance was achieved by selecting an equal number of artifactual and normal volumes.

The labeled data were used to train a 3D-CNN consisting of five 3D convolutional layers of increasing filter size and ReLu activation. Each convolutional layer is followed by max-pooling and batch normalization. The output from the last block is flattened, passed to a dense layer with 256 neurons, and then to a dropout layer to prevent overfitting. Finally, a dense layer of 1 neuron with sigmoid activation is used to perform binary classification. The model was trained for 20 epochs and a 5-fold cross-validation method was used to evaluate sensitivity to the training data.

Model robustness to a second protocol was tested with data from an ongoing study with a different data acquisition orientation. The model was re-trained on the same training data, this time zero-padded to be of size 128x128x128 and randomly reformatted to shuffle the axes. The re-trained model was used to make predictions on images acquired with the second protocol.

- **Diffusion MRI** (dMRI) techniques can produce *thousands of images* that must be manually inspected for artifacts such as motion
- Manual inspection is *time-consuming* and prone to *subjective error*
- Removing motion-compromised volumes is essential for pediatric subjects
- A **convolutional neural network** trained on 1- and 24-month-old subjects can identify artifactual volumes with ***accuracies above 90%*** using the same scan protocol

RESULTS



The labeled dataset used for this work contained 2013 and 263 volumes from 1- and 24-month subjects, respectively. Training and validation were performed on 5 unique data splits, resulting in a mean accuracy of 95±1.2%. Examples of image volumes from the same subject that were correctly identified as normal (top row) and artifactual (bottom row) are shown on the left. The accuracy results from the 5-fold cross validation are shown in the table below.

Fold #	Accuracy
1	96.8%
2	95.3%
3	95.4%
4	93.5%
5	94.3%

RESULTS (Cont.)

Preliminary results with the model re-trained using reformatted data show a decrease in accuracy on the original dataset (93±1.8%) but acceptable accuracy (80±3.4%) on an example case from a new protocol with a different acquisition orientation.

CONCLUSIONS

A DL model for binary classification can be extended to motion artifact detection in diffusion MRI of pediatric subjects. A high accuracy of 95% was achieved for a dataset of images acquired at 1- and 24-months of age using the same protocol.

This model could not be applied to data from a new protocol with a different acquisition orientation. Preliminary results show that re-training the model with a cubic imaging volume and random reformatting can allow the model to learn artifact features independently of plane and subject orientation. These results are acceptable, but in future work will be improved and tested on more data from the new protocol.

The proposed model could be used in a diffusion processing pipeline to save time and eliminate human subjectivity. Additionally, it could be implemented directly onto the scanner to let operators know to reacquire volumes when the subject has moved during acquisition.

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