AUTOMATIC DETECTION OF MOTION ARTIFACTS ON MRI USING DEEP CNN

Fantini I.[1], Rittner L.[1], Yasuda C.[2], Lotufo R.[1]
[1]Medical Image Computing Lab, School of Electrical and Computer Engineering (FEEC), University of Campinas, Brazil;
[2]Neuroimaging Laboratory, Faculty of Medical Sciences (FCM), University of Campinas, Brazil

Motivation

Motion artifacts on brain Magnetic Resonance Images (MRI) constitute an important factor that degrades the image quality, impacting the quantitative analysis based on structural segmentation for clinical research. Thus, assessing the image quality is essential to determine if the image fulfills the minimal quality level necessary to the research analysis. Nowadays an MR expert, responsible for quality control, performs a visual check on every acquired image. Usually, MRI database is huge, and its quality screening is time-consuming and fatiguing.

Objective

The proposal is to automatically detect the images containing motion artifacts using Deep Convolutional Neural Networks (CNN).

Material and Methods

- The dataset is composed of T1-weighted volumetric sequence from 68 healthy volunteers acquired in sagittal plane, divided into 2 classes: motion artifacts presence and motion-free images (Fig 4 and 5).
- The dataset was divided into 70% - 30%, at acquisition level, for training and test.
- 128x128 patches were randomly extracted from slices.
- Published networks from Keras [1] were selected: ResNet50 [2], InceptionV3 [3], Inception-ResNet [4] and Xception [5]. The method combines these four CNNs exploring the different characteristics extracted from each one.
- As convolutional filters from lower layers map smaller regions in the original input and our goal is to detect fine-grained image corruption, the CNNs were adapted to use the output from lower intermediate level as features to the binary classifier.

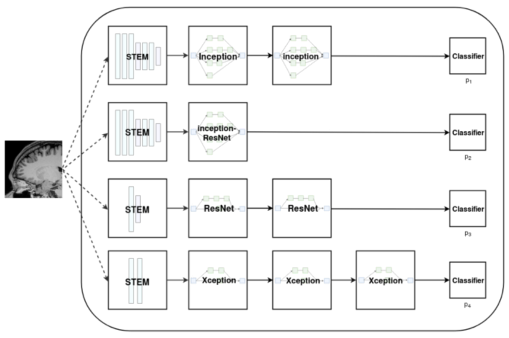

Figure 1: The four adapted models.

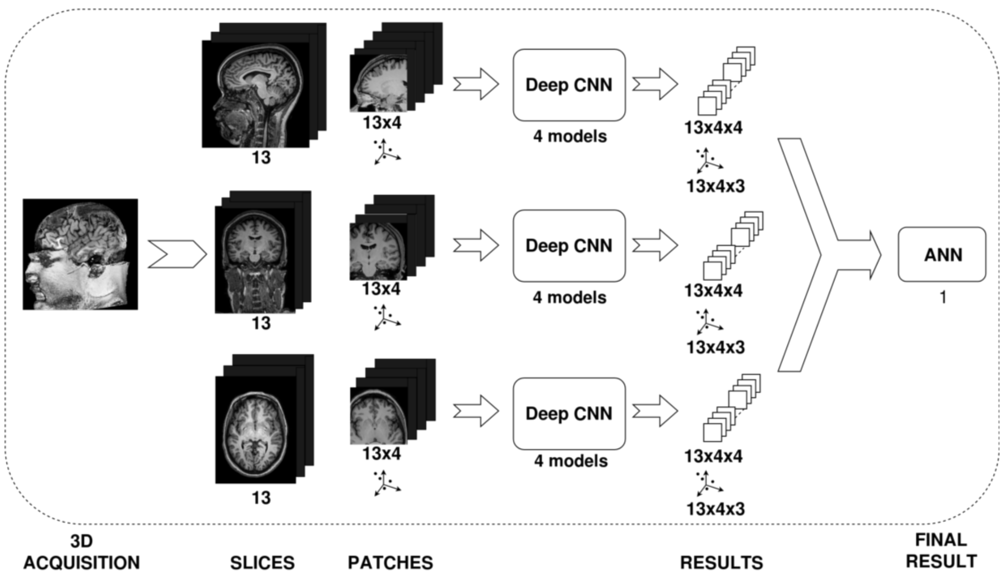

Figure 2: The method selects slices from each view of the 3D sequence to extract their patches. For each axis, results from four models are combined to detect the motion artifact presence.

Results

- To make the prediction more precise, we included the patch location information along to the four Deep CNNs probabilities. Processing these combined features, by an Artificial Neural Network (ANN), resulted in the acquisition motion presence probability (Fig. 2).
- The method used a 3-fold approach to learn the training set due to the small amount of sample data.
- The method results were predictions $p \in [0,1]$ for the presence of motion artifacts on the input image (Fig.3).
- The overall performance on the test set was 95.05% per patch and 100% per acquisition (Fig.3).

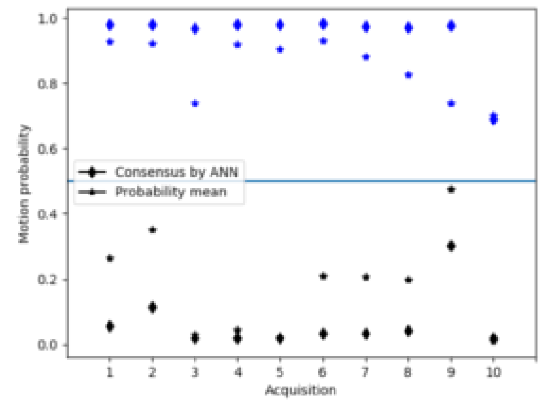

Figure 3: Probability results comparison between the proposed method (diamond) and the mean probability (star). In blue are the acquisitions containing motion artifacts and in black are the motion-free acquisitions.

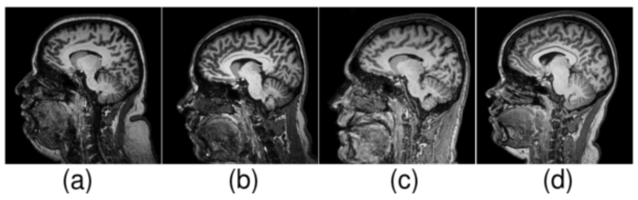

Figure 4: Motion-presence images exemplary. Correspondence to the graph (blue in fig. 3): (a) 6, (b) 9, (c) 3, (d) 10.

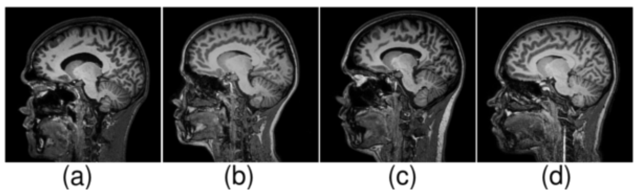

Figure 5: Motion-free images exemplary. Correspondence to the graph (black in fig. 3): (a) 5, (b) 1, (c) 2, (d) 9.

Discussion

The technique focused on detecting motion presence on MRI regardless the motion artifact severity. The variation on probabilities results suggests a correlation to the motion artifact severity level. The correctness of these probabilities results needs to be verified by testing annotated data reporting different levels of image quality.

Conclusion

The proposal to use Deep CNN to automatically detect motion artifact on brain MRI succeeded. Regarding the ability to reveal these artifacts, the technique can be applied to large datasets to provide a probability motion presence, which can be used as a scale (higher values correspond to the severity of motion artifacts) to guide a more efficient and fast removal of low-quality images.

References

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Irene H.S.P. Fantini
ihspf@dca.fee.unicamp.br

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