Automatic detection and reacquisition of motion degraded images in fetal HASTE imaging at 3T

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Synopsis

Fetal brain MRI suffers from unpredictable and unconstrained fetal motion that not only causes severe image artifacts even with single-shot FSE readouts, but also results in slice-to-slice variations of the imaging plane and long scanning sessions, as the MR technologist "chases" the fetal head in an attempt to acquire artifact-free orthogonal images. In this work, we have implemented a closed-loop pipeline that automatically detects and reacquires HASTE images that were degraded by fetal motion, without any interaction from the MRI technologist. The presented methods demonstrate the basic infrastructure needed for successful prospective automated fetal brain motion correction.

Introduction/Purpose

Fetal brain MRI suffers from unpredictable fetal motion, limiting the types of MR acquisition schemes practical for use in clinical settings to fast single-shot encoding techniques, such as HASTE. Nevertheless, even when using HASTE, fetal MRI sessions can be significantly lengthened, as fetal motion during the HASTE acquisition not only degrades image quality, but also introduces slice-to-slice variations of the imaging plane, resulting in double-oblique slices which are hard to interpret clinically. Therefore, in a typical fetal MRI session, the MRI technologist "chases" the fetal head, in an attempt to obtain images in the standard three orthogonal planes, resulting in repetition of the entire HASTE acquisition if sufficient slices in the stack are motion degraded or became double oblique. Thus, the current fetal imaging workflow depends on rapid assessment of the image stack quality and determination if it should be repeated. In this work, we designed and implemented a *prototype* closed-loop acquisition/reconstruction pipeline that automatically, without human interaction, detects and re-acquires *only* the slices that have been degraded by fetal motion, and not the whole stack.

Methods

We have previously shown the feasibility of using a convolutional neural network (CNN) engine that performs an automatic image quality assessment (IQA) of fetal brain HASTE images, and outputs a quality score[1]. In this work we developed and implemented a pipeline that runs the IQA CNN engine on a GPU (NVIDIA 1050Ti) equipped computer, connected to the scanner's internal network via 1GB Ethernet hub, for efficient communication/feedback between this computer and the scanner's computer running our custom MRI sequence and reconstruction. This setup is similar to those used for real-time neurofeedback in fMRI experiments[2–4] and prospective motion correction in neuroanatomical MRI[5,6]. The proposed methods involved modifying the HASTE sequence acquisition and reconstruction, as well as generating Python scripts that in real time receive the HASTE images, run the CNN IQA engine, and send the IQA score of each slice back to the sequence. Figure 1 shows a schematic of the overall acquisition/reconstruction engine, described below.

HASTE acquisition modification: We used an enhanced HASTE sequence, called vNav-HASTE, which embeds low resolution EPI volumetric navigators (EPI-vNavs)[7] within the TR to obtain a low resolution volume of the fetal head (5mm^3 voxels, 3D EPI readout, TA=0.7s) before every acquired HASTE slice[8]. For this project, we further modified this sequence to enable: 1. socket connection to the GPU computer for seamless transfer of the IQA scores upon sequence request during run-time; 2. reacquisition loop that starts seamlessly (without any human interaction) right after the prescribed HASTE stack is acquired, and reacquires a user defined number of slices, N_{REACQ}, with the N_{REACQ} worst IQA scores.

HASTE reconstruction modification: The online reconstruction was modified such that HASTE images are sent to the GPU computer via a socket connection as soon as they are reconstructed. Additionally, besides the original HASTE stack, the reconstruction engine outputs the N_{REACQ} reacquired images in a separate image series.

IQA scores calculation: We trained a VGG-16 network (Figure 2a) to classify HASTE images as diagnostic or non-diagnostic. The network is first pre-trained on Imagenet dataset and then fine-tuned on a fetal HASTE dataset (4432/1557 diagnostic/nondiagnostic images). To address the problem of class imbalance in MRI dataset, we adopted weighted binary cross entropy as loss function during fine-tuning. The network was evaluated on a separate test set with 1329 slices, see ROC curve in Figure 2b. With an image with size of 256x256, each IQA score is computed in 30 ms on the GPU computer used.

Phantom development and in vivo fetal scans were performed on a 3T Skyra scanner (Siemens Healthcare, Erlangen, Germany) using spine and body flex receive arrays. The vNav-HASTE-reacq sequence (TE/TR=119ms/1.8s, FOV=33x33cm^2, 1.3x1.3x3mm^3 voxels, PF=5/8, R_{GRAPPA}=2) was run on two pregnant mothers who signed informed consent forms approved by BCH's IRB.

Results

Figure 3 shows images from vNav-HASTE-reacq scan with N=10 slices and N_{REACQ}=6 slices to reacquire, showing that our sequence correctly reacquired the slices at locations where the 6 slices with the lowest IQA scores (shown in red) were originally acquired. Figure 4 shows 4 images from 3 separate scans, where the originally acquired slices were motion degraded, and the re-acquired ones were not. The IQA scores shown above the images range from 0 to 1 (0=poor, 1=excellent quality).

Discussion/Conclusion

We have demonstrated a closed-loop acquisition/reconstruction pipeline that automatically detects and reacquires motion degraded fetal brain HASTE images. The proposed infrastructure has all the necessary infrastructural capabilities for robust real-time, prospective fetal head motion correction. Specifically, our future work includes developing a computational engine capable of efficiently and reliably determining the fetal head pose from the low resolution EPI-vNavs obtained before each HASTE slice. The communication framework described here can easily be adapted to include this information for appropriate reorientation of the FOV of the next HASTE slice. Moreover, we intend to further improve the accuracy performance of the IQA CNN engine. This work is part of our greater effort and ultimate goal of developing an intelligent system that "chases" the fetal head in real-time to obtain high quality, high resolution, diagnostic HASTE images of the entire brain in the least amount of time.

Acknowledgements

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Figures

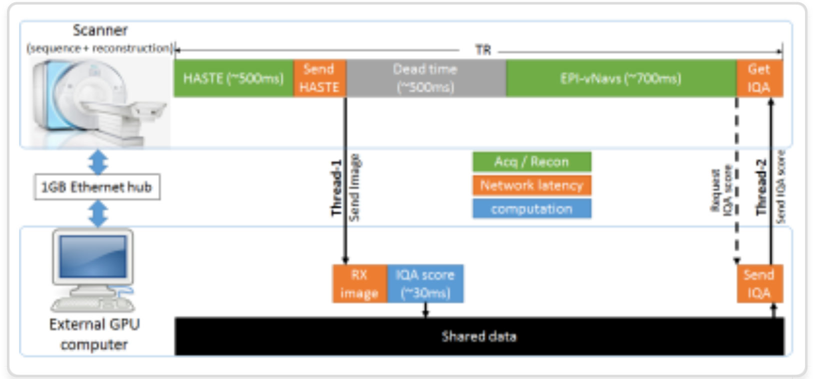

Figure 1. Schematic of the closed-loop acquisition/reconstruction framework for the vNav-HASTE-reacq sequence capable of automatically detecting and reacquiring motion-degraded fetal brain HASTE images. The scanner's computer is connected with the external GPU computer via a 1GB Ethernet hub. The GPU computer receives HASTE images in real-time, calculates the IQA score for each of them, and sends this score back to the sequence upon request during runtime.

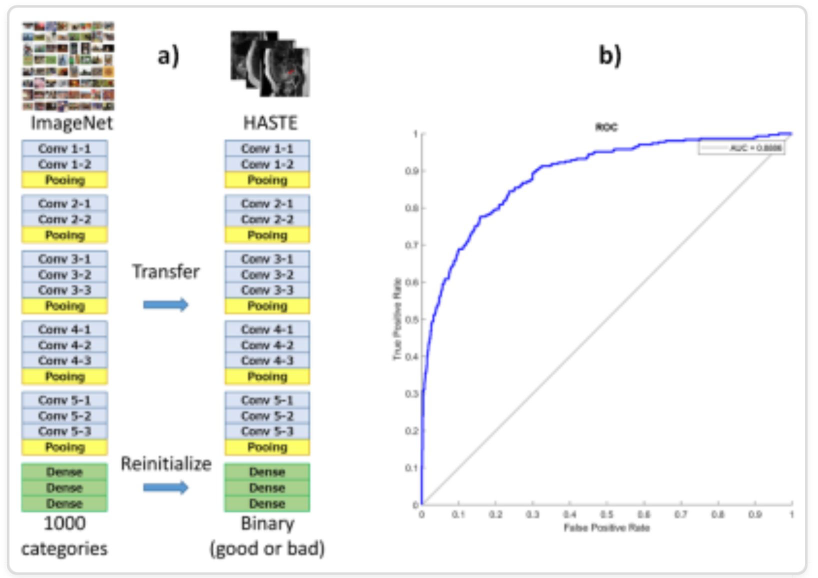

Figure 2: Training and evaluation of IQA network. (a) A VGG16 network is pretrained on ImageNet and then fine-tuned on HASTE data. (b) The ROC curve of the IQA network on test dataset. The Area Under the Curve (AUC) is 0.8886.

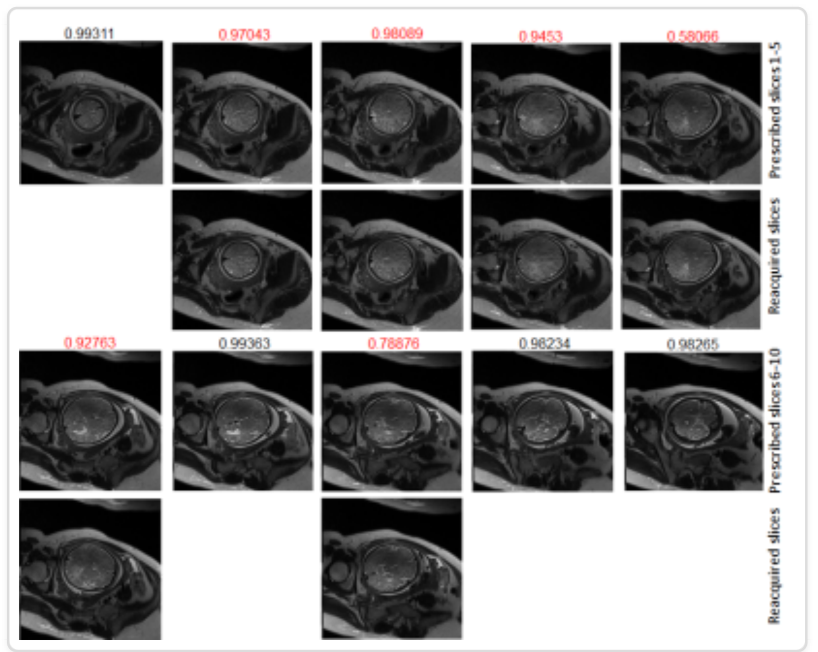

Figure 3: In vivo fetal MRI using the vNav-HASTE-reacq sequence with N=10 prescribed slices, and N_{REACQ}=6 slices to reacquire. The IQA scores of the originally acquired slices are given above the images, with 0 and 1 representing bad and good quality, respectively. The 6 lowest IQA scores are given in red, and it is these 6 slice locations which the sequence reacquired new images for, showing that the whole pipeline performs as expected. Note that no significant fetal movement was observed during this scan.

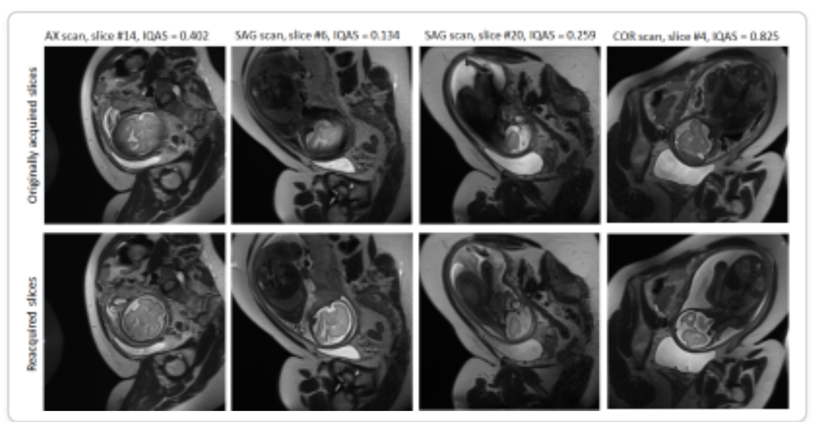

Figure 4: Four examples from three separate vNav-HASTE-reacq scans (i.e. "AX", "SAG" and "COR", with N=20 and NREACQ=10) showing motion artifacts in the originally acquired images (top row), and much cleaner images when the same slice locations were re-acquired (bottom row).