Fast Automatic Coil Selection for Radial Stack-of-stars GRE Imaging

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INTRODUCTION: For radial acquisitions of k-space, distortions of the magnetic B_0 field and gradient fields distant from the isocenter can cause significant streaking artifacts[1]. In particular if the excited object volume exceeds the region of linear gradient fields along the z-direction, it can be beneficial to disable peripheral receive coils as they often contribute mainly artifacts and add relatively little image information. However, it is difficult to tell a priori whether an individual coil image will contain reasonable information or mostly artifacts. Previous work proposed sensitivity-weighted coil combinations[2,3] or complete exclusion of coil images with high streak level[1]. In the latter approach, the decision is based on a heuristically determined threshold of a streaking-artifact measure. This has two disadvantages: First, all coil images need to be reconstructed before contaminated images can be discarded. Because gridding is the computationally most expensive part of radial MRI reconstruction, it is desirable to reconstruct only those coil images that are actually needed. Second, the classification threshold has to be determined manually for every measurement protocol.

Here, we propose a modified measure for the streak contamination that can be derived prior to the image reconstruction and, thus, saves computation time. Further, the use of k-means clustering is proposed to automatically determine the group of appropriate channels, which eliminates the need for manual selection of the artifact threshold.

THEORY: In the approach by Xue et al[1], individual coil magnitude images $\boldsymbol{I}_k$ are reconstructed first, where $k=1...K$ denotes the coil index. Then, a streaking-artifact ratio R_k is computed for every coil using Eq. (1), where $\boldsymbol{L}_k$ is an artifact-free reference image that is obtained by applying a low-pass filter to $\boldsymbol{I}_k$. A channel is classified as streaky and excluded from further processing if its streak measure R_k exceeds a heuristically determined threshold value. We modified Eq. (1) by replacing the *mean* operator (here equivalent to an L1 norm) with the L2 norm and by rewriting the difference in the numerator as a high-pass filtered image $\boldsymbol{H}_k$ obtained from $\boldsymbol{I}_k$, which gives Eq. (2).

$$R_k = \frac{mean(abs(\boldsymbol{I}_k - \boldsymbol{L}_k))}{mean(\boldsymbol{L}_k)}, \quad (1)$$

$$\hat{R}_k = \frac{\|\boldsymbol{H}_k\|_2}{\|\boldsymbol{L}_k\|_2}, \quad (2)$$

Thus, $\hat{R}_k$ corresponds to the ratio of the energy of the high-frequency coefficients to low-frequency coefficients. This criterion is intuitively reasonable because streak artifacts arise for radial undersampling and are particularly dominant if more of the signal energy is concentrated in the (undersampled) periphery of k-space. $\boldsymbol{H}_k$ and $\boldsymbol{L}_k$ can be computed either by applying a 2D low-pass filter to the gridded k-space or by applying a 1D low-pass filter to the ADC samples before the gridding operation. Due to Parseval's theorem, the L2 norm of $\boldsymbol{L}_k$ and $\boldsymbol{H}_k$ can be computed also in the corresponding k-space domain, $\boldsymbol{l}_k$ and $\boldsymbol{h}_k$. Gridding reconstruction also comprises density compensation, usually implemented as multiplication with a ramp filter in k-space. However, we neglected this step because the weighting is identical for all channels.

Hence, Eq. (3) is obtained for the approximate streaking-artifact ratio, where $\boldsymbol{h}_k$ and $\boldsymbol{l}_k$ are approximations of the high-frequency and low-frequency k-space coefficients, obtained by applying a 1D box filter to the radial k-space samples. Because the angles in a subset of a golden-angle radial acquisition are again approximately uniformly distributed, also a reduced number of readouts can be used here.

$$\tilde{R}_k = \frac{\|\boldsymbol{h}_k\|_2}{\|\boldsymbol{l}_k\|_2}, \quad (3)$$

In order to classify good versus streak-contaminated channels, a k-means clustering algorithm has been applied[4]. It is based on the idea that channels of the same class should have similar values of $\tilde{R}_k$ (high intra-class similarity) and that the $\tilde{R}_k$ values of both classes are clustered at different mean values (high inter-class distance). The channels are initially labeled with random class labels and iteratively assigned to the class associated with the closest cluster center. If the distance between the final cluster centers is less than twice the average standard deviation, no channels are excluded. Otherwise, the channels in the cluster with the higher cluster-center value (average $\tilde{R}_k$) are discarded.

METHODS: The proposed method was evaluated for 20 slices with prominent artifacts, selected from 13 volunteer scans. The datasets were acquired on different 1.5T and 3T MR systems (Siemens Healthcare, Erlangen, Germany) using a 3D stack-of-stars GRE sequence with golden-angle reordering and coronal slab orientation, but otherwise varying protocols. A 1D low-pass box filter with a width of 64 samples was used to filter $N=min(N_{\mathrm{mat}}, N_{\mathrm{acq}})$ radial spokes of every slice, where N_{mat} is the reconstructed image size and N_{acq} is the number of acquired radial spokes. The energy was computed for each channel using Eq. (3). 10 iterations of the k-means clustering algorithm were found to be sufficient for the channel classification.

RESULTS AND DISCUSSION: For all tested datasets, the sum-of-squares combination using only the selected channels exhibited less streaking artifacts than the reconstruction using all acquired channels. An example is shown in Fig. 1. Three of the single-channel images are significantly affected by streak artifacts (c, d, f), which is reflected by the proposed streak measure (channels 3, 4, 6 in Fig. 1h). The classifier reliably detected and discarded such outliers, resulting in reduced streaking of the sum-of-squares combined image (j) compared to the reconstruction of all channels (i).

A limitation of the method may arise for certain coil geometries from the proposed approximate streak ratio $\tilde{R}_k$, which for a given channel describes the fraction of signal energy contained in the higher frequencies. High inter-class distance is valid if all receive channels have similar field-of-view (FOV), but may be violated if some receive coils have extremely localized sensitivities compared to the others. In this case, it is still possible to employ the proposed classification technique using the original streak measure R_k, albeit at higher computational cost.

CONCLUSION: This work proposes a measure for streaking artifacts in single-coil images that can be used to exclude individual coils from the reconstruction. It is highly efficient because it can be computed from a subset of the acquired raw data and does not require intermediate image reconstruction. Unsupervised k-means clustering is employed to automatically detect and discard channels that are particularly affected by streaking.

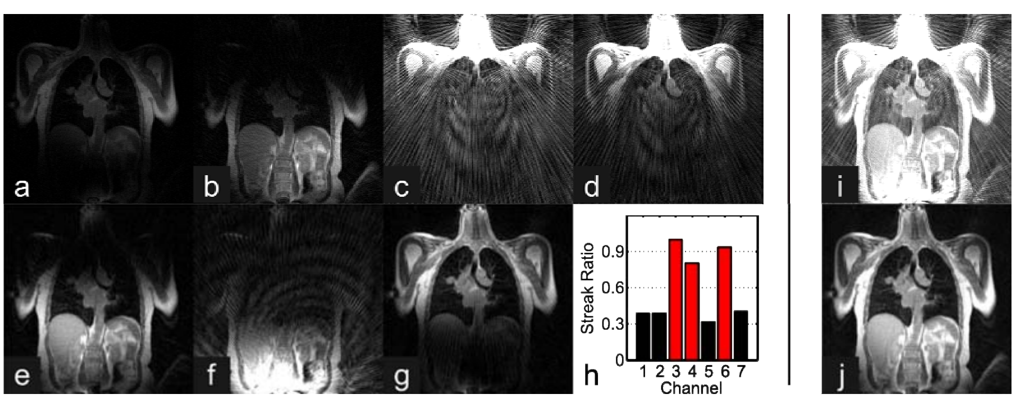

Fig. 1: a-g) Individual coil images 1-7,
h) Approximate streaking ratio $\tilde{R}_k$,
i) Combination of all channels,
j) Combination of accepted channels (black in Fig. 1h).

All images are displayed in the same range.

REFERENCES:

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