Correction of RF spike noise in MR images using Robust Principal Component Analysis

Adrienne E Campbell-Washburn[1,2], David Atkinson[3], Oliver Josephs[4], Mark F Lythgoe[5], Roger J Ordidge[6], and David L Thomas[7]
[1]*Centre for Advnaced Biomedical Imaging, University College London, London, London, United Kingdom,* [2]*Department of Medical Physics and Bioengineering, University College London, London, United Kingdom,* [3]*Centre for Medical Imaging and Centre for Medical Image Computing, University College London, London, United Kingdom,* [4]*University College London and Birkbeck College, London, United Kingdom,* [5]*Centre for Advanced Biomedical Imaging, Division of Medicine and Institute of Child Health, University College London, London, United Kingdom,* [6]*Centre for Neuroscience, University of Melbourne, Melbourne, Victoria, Australia,* [7]*Department of Brain Repair and Rehabilitation, UCL Institute of Neurology, University College London, London, United Kingdom*

TARGET AUDIENCE: This artefact correction algorithm will be of use to researchers faced with RF spike noise

INTRODUCTION AND PURPOSE: Striping artefacts in MR images can severely degrade image quality. These artefacts are caused by RF noise from hardware problems such as vibrations, loose connections or improper shielding of RF coils, producing high intensity RF spikes in k-space [1]. Ideally, imperfections in hardware should be addressed promptly; however, in practice, data is sometimes acquired when these faults are present and the resulting artefacts must be removed in image post-processing [1-5]. This abstract presents a method for the semi-automated detection and correction of RF spikes using Robust Principal Component Analysis (RPCA) [6] in combination with a refilling of the central k-space cluster.

METHODS: Algorithm: RPCA aims to decompose a measured matrix (**M**) into a low-rank matrix (**L**) and a sparse matrix (**S**), which can have arbitrarily large entries, by solving: $\min_{L,S} \|\mathbf{L}\|_* + \lambda\|\mathbf{S}\|_1$ such that **M** = **L**+**S**, where $\|\cdot\|_*$ represents the nuclear norm of a matrix and $\|\cdot\|_1$ represents the L1-norm of a matrix. In the case of RF spike noise, **M** represents the measured data, **S** represents the high intensity RF spikes, and **L** represents the recovered 'artefact-free' k-space data. RPCA was performed in MATLAB R2008b, Student Version (Mathworks, USA) using the "inexact_alm_rpca.m" [7] based on the algorithm presented by Lin et al [8]. We modified the "inexact_alm_rpca.m" algorithm to accept complex k-space time-series data. K-space is highly peaked near the centre and here we multiplied the default value of λ [6] by a factor that increases the sparsity penalty. The central region of k-space can be incorrectly classified as sparse, and we used the MATLAB function "bwlabel.m" with default 8-connectivity to detect the central cluster of k-space points in **S**, and refilled this cluster in **L**.

Application: The despiking algorithm was applied to data acquired at 9.4T (Agilent Technologies, Santa Clara, USA) using a malfunctioning volume resonator coil. Images from T_1 mapping in the mouse heart and kidney, as well as cine images, were corrected using the algorithm.

To confirm that despiking did not alter signal intensity or quantitative T_1 estimation, the procedure was applied to 8 artefact-free data sets, and myocardialT_1 quantification was compared before and after application of the despiking algorithm. In order to validate that the despiking algorithm effectively recovered the artefact-free k-space, simulated RF noise corruption was added to an artefact-free T_1 data set, and the despiking procedure applied. To simulate RF noise, a random number and distribution of high intensity spikes were added to the artefact free data set, with rise/decay in the readout direction (to mimic experimental observation). The myocardial T_1 and noise standard deviation were compared between the original data, synthesized spike noise data and despiked data. Noise standard deviation was used as a metric of artefact-level, since the stripes create an increased variation in the noise. This was repeated for 10 synthesized data sets.

RESULTS: The optimal multiplication factor used to adjust λ [6] was 5 for all applications. A clear improvement in image quality and k-space RF spikes is observed following despiking algorithm (Figure 1). Applying the despiking procedure to artefact-free data sets did not change myocardial T_1 estimation, $T_{1after} = 0.97T_{1before}+0.06$. Adding simulated RF spikes data sets changed T_1 values compared to original values by 40.0 ± 20.8 ms, and applying the despiking procedure regained T_1 values to within 3.2 ± 2.9 ms of original values. Similarly, the noise standard deviation was increased by 46 ± 25% in the synthesized spike noise data, and despiking returned this to within 1 ± 1% of the original value.

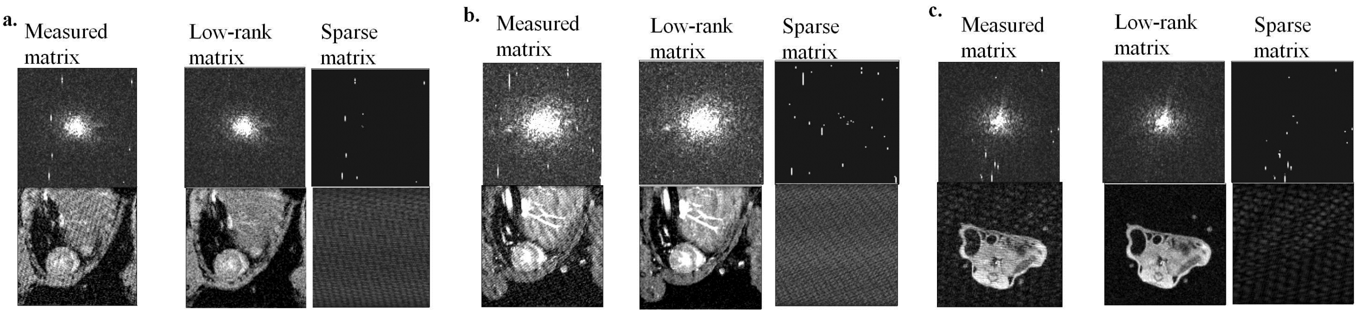

Figure 1: Example application of RPCA despiking procedure with central k-space cluster re-filling on a) myocardialT_1mapping data set, b) cine images and c) kidney T_1 mapping data set. The k-space matrix (top row) and the image after Fouier Transform (bottom row) is shown for the original measured k-space and the decomposed low-rank and sparse matrices. Images from sparse matrix are scaled differently to highlight stripes. The sparse matrix includes only the RF spike data and the low-rank matrix is free of high intensity spikes. Striping artefact is clearly removed from low-rank matrix images.

DISCUSSION: Here we have demonstrated the potential of RPCA, in combination with an automatic k-space centre refilling, to effectively decompose k-space corrupted by RF spikes into the artefact-free and spiked k-space components to regain image quality and quantitative T_1 information. The only non-automated step to this procedure is the choice of multiplication factor used to adjust default λ. Here we found that a multiplication of 5 was effective for our data sets, however this would need confirmation for each new data type. Application to cine images (Figure 1b) left more residual spike contamination in **L**, perhaps due to the broader k-space distribution; however, these lower intensity residual spikes do not affect corrected image quality. The matrix **L** was found to remain full rank, equal to the number of frames in each application, perhaps due to noise in data.

Previously, we have presented a Fourier Transform based method of detecting RF spikes in k-space [5]. However, this previous method required the manual selection of an ROI outside the object and the optimization of 3 parameters, meaning that this RPCA-based technique is more automated. In addition, the use of 3D Fourier Transforms resulted in the potential for false-positive detection in the readout and frame directions.

In conclusion, we have presented here an RPCA-based method of separating RF spike noise from corrupted time series data sets which can be used to correct striping artefacts in post-processing.

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