

# A Multi-Resolution Adaptive Filtering for Preserving Information in Dynamic Functional Imaging

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**SYNOPSIS:** The noninvasive, *in vivo* characterization of the tumor vasculature using dynamic MRI is an indispensable tool in the study of the tumor microenvironment. However, irrespective of the models employed when creating functional maps of the tumor vasculature, we often lose voxels to noise or to poor fitting. Here we propose an approach wherein, voxels that do not meet the criteria for goodness-of-fit are clustered with those that do, to create a multi-resolution functional map. In such a map, the noisy voxels are rendered with lower spatial resolution, whereas the high resolution is preserved for non-noisy voxels.

**INTRODUCTION:** During dynamic functional imaging protocols, we often have to exclude noisy voxels from any eventual analyses, in spite of these voxels occurring within our region of interest (ROI). Whether the noise arises from the scanner or from some other part of the imaging protocol, it often results in significant voxel-dropout from the final functional images, be it fMRI or any kind of contrast-enhanced MR protocol. Here we propose a method for “rescuing” noisy voxels from the ROI using a combined clustering and adaptive filtering approach. Here we identify clusters of voxels that were eliminated during post-processing due to standard linear filtering and consideration of their corresponding  $R^2$  values. These voxels were then smeared out by convolution with a box-car function and re-fit with the same criterion as the non-noisy voxels. The final resolution of the resulting map was much coarser than the original dataset. The final image, obtained by combining the original functional dataset and the coarser “rescued” dataset now allows us to see any apparent trends in the ROI albeit at varying resolution.

**METHODS:** Image data obtained from an MDA-MB-231 tumor implanted in the mammary fat pad of the SCID mouse consisted of an  $M_0$  map and 3 saturation recovery maps with recovery delays of 100, 500, and 100ms. Multislice saturation recovery images were acquired with a single-shot FLASH technique;  $M_0$  map was measured with a recovery delay of 7s. Initially all images were filtered with an amplitude filter with the threshold set at 7% of the maximum  $M_0$  value. Following linearization the data sets were additionally filtered using the  $R^2$  of the regression of signal intensity vs. recovery delay. The resulting data were processed to generate a pixel-by-pixel  $R1(1/T1)$  map, with the remaining pixels set to zero. We detected a significant number of pixels that passed through the noise limiting amplitude filter but were rejected by  $R^2$  filter. To rescue these pixels we first applied a low-pass (box-car) filter to the original data set, followed by masking of the image with the difference mask (i.e. difference between the amplitude and  $R^2$  filters – blue box).  $R1$  maps were generated for the rescued pixels as before.

**RESULTS:** Blue border box demonstrates pixels that passed the amplitude filter and were rejected by the  $R^2$  filter with removal of small clusters. The orange-bordered box shows the  $R1$  map for non-noisy pixels (pixels from the blue and orange boxes are mutually exclusive). The grey-bordered box shows the  $R1$  map for the rescued pixels (from the blue box) that passed the second  $R^2$  filter. Filtering the rescued pixels with a box-car kernel improves their signal-to-noise ratio while simultaneously decreasing the resolution of the resulting  $R1$  map (grey box). Finally, the green box shows a composite image produced by combining the high- and low-resolution  $R1$  maps (i.e. orange and gray images). The low-resolution pixels are color coded red.

**DISCUSSION/CONCLUSIONS:** The developed technique produces multi-resolution maps that retain the functional information within the ROI. This algorithm is equally applicable to functional time-course data sets of different types, such as relaxation data, dynamic contrast data etc.

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