

# Selective Evaluation of Fast MRI Reconstruction Artifacts using Case-PDM

J. Miao<sup>1</sup>, and D. L. Wilson<sup>1,2</sup>

<sup>1</sup>Biomedical Engineering, Case Western Reserve University, Cleveland, Ohio, United States, <sup>2</sup>Radiology, University Hospitals of Cleveland, Cleveland, Ohio, United States

## INTRODUCTION

The perceptual difference model (Case-PDM) is being used to quantify image quality of fast, parallel MR acquisitions and reconstruction algorithms by comparing to slower, full k-space, high quality reference images. Case-PDM objectively, quantitatively evaluates image quality, and we have found it to be quite useful in investigations of keyhole, spiral, SENSE, and GRAPPA applications [1-4]. To date, most perceptual difference models average image quality over a wide range of image degradations. Here, we create metrics weighted to different types of artifacts. The selective PDM is tuned using test images from an input reference image degraded by noise, blur, or aliasing. Using an objective function based on the computation of diffusivity and edges applied to the output perceptual difference map, cortex channels in the PDM are arranged in a matrix and weighted by a 2D Gaussian function to ensure maximal response to each artifact in turn. We design human subject experiment to validate the results in the context of MR image quality evaluation. The experiments covered three different input MR images (brain, cardiac, and phantom) and three MR reconstruction algorithms (SENSE, spiral, and GRAPPA). 120 reconstructions and 7 human subject trials were used in the experiments.

## METHODS

The cortex filter matrix (6 spatial orientations by 6 spatial frequencies) of Case-PDM is weighted by a 2D Gaussian function to have high response values at specific image artifacts (e.g. noise, blur, and aliasing). To find the appropriate weighting function we created noise (or blur/aliasing) only test images from input reference image, and exhaustively searched for the function that maximizes (or minimizes in the case of blur) the diffusivity [5] (or maximizes the edges in the case of aliasing) of the output visual difference map. Therefore, the Case-PDM output can be partitioned into noise, blur, or aliasing effect visual difference maps. A scalar PDM score is obtained by summarizing the visual difference map over an ROI. A modified DSCQS (Double Stimulus Continuous Quality Scale) experiment was designed (GUI is shown in Fig. a) to obtain human subject ratings (i.e. overall, noise, blur, and aliasing ratings). The experiment covered 3 different images (brain, cardiac, and phantom) and 3 MR image reconstruction algorithms (SENSE, spiral, and GRAPPA). In total, 120 test images covering a wide range of image quality were evaluated (40 test images for each of the 3 datasets). There were 7 human subjects participating in the experiment (4 engineers and 3 radiologists). Linear correlation coefficients were calculated from pairs of human ratings and PDM scores among the test images.

## RESULTS

We found that both the average PDM score and the proposed weighted PDM score have good correlation with human subject ratings. For 3 different images (brain, cardiac, and phantom), averaged  $r$  values [PDM, noise-PDM, blur-PDM, aliasing-PDM] were  $[0.933 \pm 0.018, 0.938 \pm 0.015, 0.727 \pm 0.106, 0.500 \pm 0.193]$  and were comparable to the corresponding averaged inter-subject correlation coefficients  $[0.936 \pm 0.028, 0.856 \pm 0.064, 0.539 \pm 0.230, 0.767 \pm 0.125]$  respectively. From the optimal 2D Gaussian weighting functions, high spatial frequency channels of PDM's cortex filter matrix were more weighted than the low spatial frequency channels to have a maximal response to noise image degradation; while low spatial frequency channels are more weighted than high spatial frequency channels to have a maximal response to blur or aliasing artifact. By using this method, the PDM's visual difference map between a reference image (Fig. b) and a test image (Fig. c) can be disintegrated into a noise-effect visual difference map (Fig. e), a blur-effect visual difference map (Fig. f), and an aliasing-effect visual difference map (Fig. g) with a weighted PDM score ratio (noise-PDM : blur-PDM : aliasing-PDM) of 1:0.47:1.37, as compared to the average visual difference map (Fig. d).

## CONCLUSION

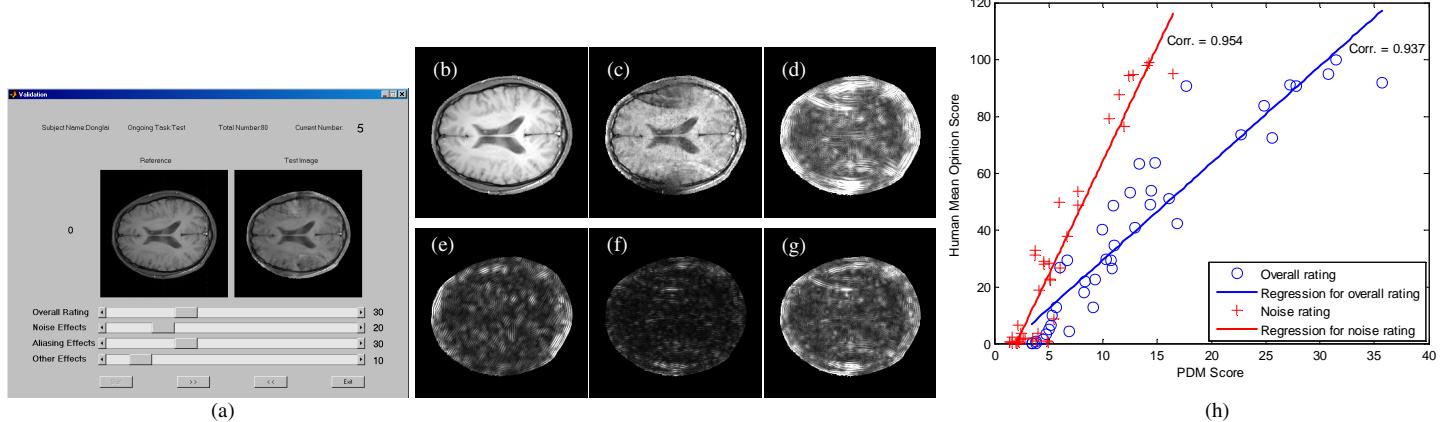
We conclude that for image quality ratings, the proposed weighted Case-PDM can faithfully represent the human subject evaluation of MR image noise and blur artifacts over a wide range of image quality with a possible exception of aliasing artifact. With continued fine tuning, we believe that the weighted Case-PDM score will be useful for selectively evaluating artifacts in fast MR imaging.

## ACKNOWLEDGEMENT

This work was supported under NIH grant R01 EB004070 and the Research Facilities Improvement Program Grant NIH C06RR12463-01. We thank the subjects for participating in the experiments.

## REFERENCES

[1] Salem et al., Journal of Electronic Imaging, 2002 [2] Huo et al., MRI 2006 [3] Huo et al., JMRI 2008 [4] Miao et al., Medical Physics 2008 [5] Zhang et al., IEEE Transactions on Medical Imaging 2007



**Figure** The GUI for a task of an image quality rating for different effects is shown in (a). The subjects needed to compare the test image (on the right side) to the reference image (on the left side), and give a scalar number (0-100, with 0 the best) to indicate the image quality for overall, noise, blur, aliasing, and other effects. The average PDM output is in (d), as compared to the weighted PDM outputs of noise effect in (e), blur effect in (f), and aliasing effect in (g). The correlation between weighted PDM scores and human ratings is good as indicated in the plot (h).