

# PCATMIP: Enhancing Signal Intensity in DW-MRI

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**Introduction:** Diffusion-weighted MRI (DWI) studies generally lose signal intensity to physiological motion, which can adversely affect quantification and diagnosis. Averaging over multiple repetitions, often used to improve image quality, does not eliminate the signal loss. In DWI, physiological movement of anatomical features can be corrected for with non-rigid-body registration software packages [1]. But bulk motion also causes phase shifts and phase dispersion in image voxels which never repeat precisely, leading to fluctuating intensity losses. The intensity fluctuations are smoothed out when averaging approaches are used; hence, while an increased signal-to-noise ratio is achieved, the local signal intensity is dampened. This gets trickier at higher b-values where the motion sensitivity of the pulse sequence is particularly high, resulting in erroneous diffusivity values and potentially incorrect clinical diagnosis. In this abstract, we present PCATMIP, a combined Principal Component Analysis (PCA) and Temporal Maximum Intensity Projections (TMIP) approach, which attempts to address this problem. **Premise:** The basic idea of PCATMIP is that when the same DWI acquisition is repeated over time, the signal at each pixel fluctuates due to several factors. First is the physical movement of the anatomical features due to physiological motion. This can be effectively corrected for with non-rigid-body image registration. However, intensity fluctuation still exists due to two other factors: bulk motion-induced intensity attenuation and random noise. We need to reduce or remove the random noise so as to be able to pick out the maximum signal and regard it as the one with minimum motion-induced loss. For this, we exploit the fact that physiological motion is mostly cardiac and respiratory, which are mechanically transmitted to other areas. Therefore, motion-induced signal fluctuations in neighboring pixels are temporally correlated, while random noises are not.

**Methods: Approach:** First, a number of repetitions (N) of 2D diffusion-weighted images  $I(x, y, m)$  (where  $m=0, 1, \dots, N-1$ ) are acquired. Utilizing a sliding window implementation of a localized boxcar ( $I_{bc}(a, b, m)$  where  $3 < a \leq 23$  and  $3 < b \leq 23$ ), the Hermitian matrix is then generated over the boxcar. Diagonalization of this Hermitian matrix yields the eigenvalues  $e_i$  and eigenvectors  $V_i(m)$ . Using these eigenvectors, the principal components (PC) over the subregion,  $P_j(a, b)$ , are  $P_j(a, b) = \sum_m I(a, b, m) V_j^*(m)$ . Subsequently, we select the first  $f$  PCs corresponding to eigenvalues greater than the noise floor,

$\epsilon_f > \beta \langle \epsilon \rangle_{N-f}$ , ( $\beta$ : threshold multiplier,  $\langle \cdot \rangle$ : average,  $f$ : number of eigenvalues selected to be accepted) and reconstruct the PCA-filtered intensity. Thus,

$I'(a, b, m) = \sum_{k=0}^{f-1} P_k(a, b) V_k(m)$  (typically  $f = 1$  or  $2$ ). This process is repeated with a sliding boxcar process, in which the center  $(p, q)$  of the boxcar is moved

over the entire image one pixel at a time. In doing so, each pixel  $(x, y)$  is covered by many boxcars and each boxcar generates a set of filtered intensities  $I'_{pq}(x, y, m)$ . At each pixel, these boxcars are combined in a weighted sum to yield the final PCA-filtered image intensity for pixel  $(x, y)$  and the  $m^{\text{th}}$  repetition:  $I_{PCA}(x, y, m) = \sum_{p, q} w(x - p, y - q) I'_{pq}(x, y, m)$  where the weight  $w$  decreases with increasing distance between  $(x, y)$  and  $(p, q)$ . Subsequently, a

pixel-wise temporal maximum intensity projection (TMIP) operation yields the final image:  $\Theta(x, y) = \max_{m=0}^{N-1} (I_{PCA}(x, y, m))$ . **Numerical Simulations:** To

validate the PCATMIP approach and determine the parameters for optimal operation, we performed numerical simulations using a phantom with two non-overlapping zones with the signal intensities of the two zones fluctuating independently and Rician noise added-in. **Experiments Performed on a 1.5T Siemens Avanto scanner:** To determine the noise threshold, a noise image was acquired in absolute mode using a FLASH sequence. An agarose-water phantom was also used to generate experimental DWI images to validate ADC numbers. Subsequently, we acquired DWI data with ten repetitions of the DWI sequence on a Yorkshire pig anesthetized using isoflurane and scanned in accordance with ACUC regulations in respirator-controlled breathing mode, with b values of 0, 200, 400 and 800 s/mm<sup>2</sup>. Also, to test the stability of PCATMIP method, we acquired 40 repetitions of the DWI sequence and randomly

divided these into 6 groups of ten repetitions. Two-dimensional non-rigid registration was performed for all datasets acquired to correct for bulk motion before processing by averaging, TMIP or PCATMIP approach.

## Results and Discussion:

Numerical simulation shows that the root-mean-square-error (RMSE) for PCATMIP stabilizes to less than 4% for boxcars greater than 15 x 15. Also, the ratio of

the first eigenvalue to the last 8 eigenvalues from the noise image shows that  $\beta$  equals 40 for  $f$  of 2. The agarose phantom DWI data processing yielded identical ADC maps with PCATMIP and averaging ( $2 \times 10^{-3}$  mm<sup>2</sup>/s), while the ADC value obtained by TMIP is smaller than that obtained by either PCATMIP or averaging. Figures 1 to 4 show the results for porcine liver DWI. PCATMIP yields 11 – 18% higher signal intensity (SI) relative to the averaging method (Fig. 1) and has SNR approaching that of averaging for  $b > 0$  (Fig. 2). Also, processing the 6 randomized porcine diffusion datasets showed that the liver ADC measurement variability was reduced by 59% by PCATMIP versus averaging (Fig. 3). Figure 4 shows the trace-weighted axial images obtained by the TMIP, PCATMIP and averaging. PCATMIP has similar noise level to averaging but higher signal intensity than averaging; on the other hand, TMIP had higher SI but higher noise. Thus, PCATMIP yields an optimum between averaging and TMIP: it achieves higher SI than averaging and higher SNR than TMIP, and is less variable than averaging.

**References:** 1. Chef'd'hotel C, et al. CompVis-ECCV 2002, 2350:251-265.

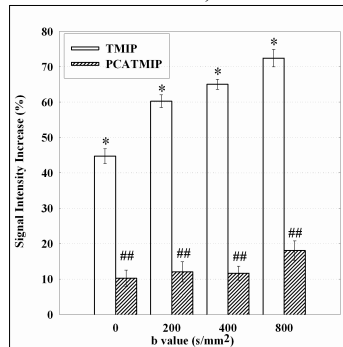


Figure 1. DWI signal intensity increases by TMIP and PCATMIP (\*:  $P < 0.001$ , ##:  $P < 0.03$  for  $b=0$  and  $P < 0.001$  otherwise)

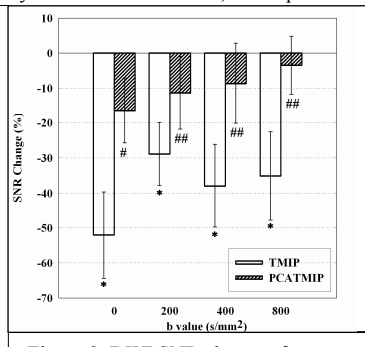


Figure 2. DWI SNR changes from TMIP and PCATMIP relative to averaging. (\*:  $P < 0.002$ , #:  $P = 0.03$  for  $b=0$  and ##:  $P = 0.33$  for  $b > 0$ )

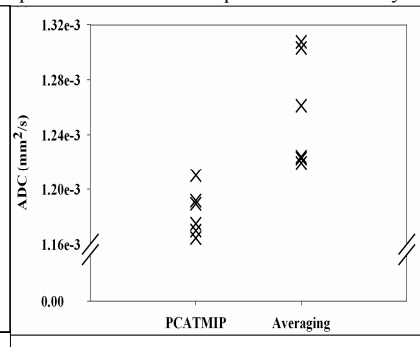


Figure 3. ADC values determined by PCATMIP and Averaging for six randomized porcine diffusion datasets.

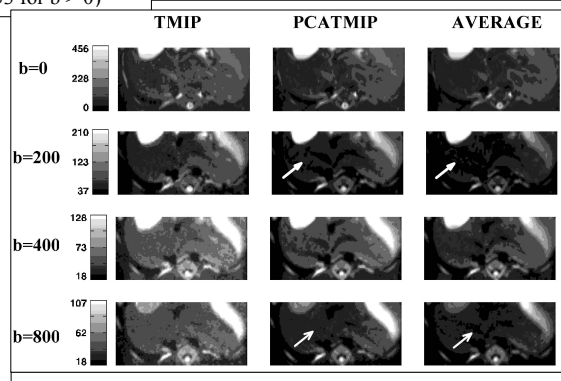


Figure 4. Trace-weighted axial images from a porcine DWI scan for 4 b-values used: 0, 200, 400 and 800 s/mm<sup>2</sup>.