Motion Estimation from Noise Intrinsic Correlation between RF Channels (MECHANICS)

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Target Audience: MR researchers and clinical scientists working with dynamic MRI studies (DCE, Diffusion MRI, fMRI, etc.)

Introduction: Accurate and efficient motion estimation is critical in MRI studies to achieve better anatomical resolution and faithful physiological analysis [1-4]. However, existing quantitative motion estimation/correction (ME/MC) methods require additional hardware or additional time cost of navigator or intensive registration. Here we propose a new method that accurately estimates motion using the motion-induced changes in noise correlation existing in all multi-channel MRI signals. This approach enables real-time and post-scan motion estimation without modifying acquisition or adding equipment, complements other ME/MC methods and is contrast-independent.

Theory: Motions induce changes in the noise correlations between RF coil arrays (shown in Fig.1). Intrinsic noise [5] is the noise voltage originating from eddy currents induced in the sample and is the dominant source of the noise correlation between signals from RF coil arrays. It can be formulated as in Eq.1 and the intrinsic correlation coefficient is largely related to the sensitivity function **S** depends on position of RF receiver and samples. We make uses of the motion-induced changes in intrinsic noise correlation in multi-channel MRI signals as an intrinsic navigator of motion. Here the motion model is simplified as rigid motion in the method but further extension was also discussed.

$$\rho_{i,j} = \frac{E[N_i N_j]}{\sqrt{E(N_i^2)E(N_j^2)}}, N_i(t) \sim \int_{\vec{r}\in V} S_i(\vec{r}) M_N(\vec{r},t) f_E(\vec{r},t) d\vec{r} + n_i(t) \sim \int_{\vec{r}\in V} S_i(\vec{r}) M_N(\vec{r},t) d\vec{r} \text{ if no encoding} \quad (1)$$

ρ: Correlation Coefficient; **E:** expectation; $\mathbf{N_i}$: Noise acquired, $\mathbf{M_N}$: Noise sample induced from sample; $\mathbf{f_E}$: Encoding weights; **S**: Weights depending on channel-sample positioning; $\mathbf{n_i}$: Uncorrelated noise

Methods: **Motion Estimation: 1) Noise Correlation Matrix** was computed from either *k*-space or image domain signals. Noise correlations between raw *k*-space noise from multi-channel MR signals were estimated using *Person's correlation coefficient* $\rho(x,y) = cov(x,y)/\sqrt{var(x)var(y)}$. For image domain extraction, reconstruction was conducted using the signal in certain time window and the correlation coefficient of background signals (extracted by threshold) from different channels was computed.

2) An encoding model was used to estimate motion from the noise correlation matrix. The noise correlation information has much higher dimension than the motion parameters (translation *T* and rotation *R*) for which conventional methods may fail. In our method, firstly, for each channel pair, we trained a model $\rho_{i,j} = \boldsymbol{f_{i,j}}(T,R)$ encoding the correlation coefficient with motion information. A 2nd-*order* model was fitted which is consistent with the physical formula of the intrinsic noise correlation. Secondly, given any correlation coefficient value and motion parameters we can estimate the likelihood $L_{f_{i,j}}(\rho_{i,j}|T,R)$ based on the trained model. Thirdly, an optimization strategy was used to search the optimal translation and rotation parameters that maximize the sum likelihood among all channel pairs. The optimal translation and rotation is the final output of the estimated rigid motion parameters. $(\boldsymbol{T_{opt}}, \boldsymbol{R_{opt}}) = \boldsymbol{argmax} \sum_{i,j} \boldsymbol{L_{f_{i,j}}}(\boldsymbol{\rho_{i,j}}|\boldsymbol{T},\boldsymbol{R})$.

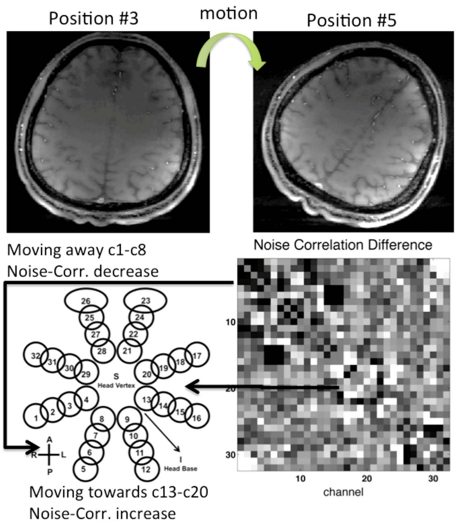

Figure 1. The physical illustration of the motion-induced noise correlation changes. An example of position changing of brain shown in top row. The motion can be estimated from the motion-induced noise correlation changes shown in right-bottom. The changes have clear physical meaning shown in left-bottom.

Motion Estimation Performance for Different Settings

DATA/NOISE SOURCE	SAMPLING ACCERATION	TEMPORAL RESOLUTION		ESTIMATION ACCURACY	
		Sample	Time(ms)	Trans.(mm)	Rot.(°)
3T, raw	-	1000	*20.7*	1.09	9.8
3T, image	full	50	*10.3*	4.10	*3.7*
3T, image	R=4	500	*103.3*	3.06	*4.3*
7T, raw	-	1000	*20.7*	1.51	9.4
7T, image	R=4	500	*103.3*	1.02	1.9

Table 1. The estimation accuracy and effective temporal resolutions: Millimeter level translation and degree level rotation accuracy is achieved. The method utilizes the noise correlation from either raw noise acquisition or extraction from reconstructed image. Further acceleration can improve the effective temporal resolution.

Experiments: The method was evaluated on both 3T MR750 and 7T MR950 GE Whole Body MRI scanners with 32-channel head coil on a healthy volunteer. MP-RAGE sequence (TE/TR/TI/Readout=3.2/2500/1100/1000ms, α=18°, 30 slices, FOV=192mm×192mm, matrix size=256×256, slice thickness=0.8mm) was adopted to acquire full k-space data at 7 different head positions (two poses shown in Figure 2). The datasets were fully sampled and retrospectively under-sampled offline to simulate the effect in accelerated acquisition with ESPIRiT reconstruction [6].

Noise Data: Here we evaluated and compared the method from both raw noise and extracted image domain noise. For each position, we collected raw noise samples from a pure noise scan without encoding and with zero flip angle. We also reconstructed the T1w brain scan and extract the background samples as noise with a threshold (outside image support and within 10% of maximum intensity).

Results: Prospective image registration results based on T1w brain scans were used as a ground truth estimation of motion. We quantified the accuracy of the proposed method using Root-Mean-Square-Error (RMSE) of motion parameters. Multiple settings were compared: 1) using noise extracted from *k*-space or image domain, 2) whether to use acceleration which improved temporal resolution of the estimation for image domain method 3) how many samples to use for each estimation which effect both the equivalent temporal resolution and accuracy. Shown in the table below, the proposed algorithm achieves 1mm accuracy in translation and about 2~3 degree accuracy in rotation while with temporal resolution (equivalent time cost for each estimation computed based on read-out time cost) is 20~100 milliseconds.

Discussion: The proposed method does not require further acquisition, hardware and is not affected by contrast changes. The change of correlation coefficient has clear physical meaning (Fig.1). This approach is applicable for both on-line and off-line ME/MC and compliments other navigators and motion estimation methods. Non-rigid motions can be estimated with further modeling.

References: [1] Jenkinson 2002 [2] Zaitsev 2006 [3] Kober 2011 [4] Cheng 2012 [5] Constantinides 1997 [6] Uecker 2013