Predictive sensor for real-time respiratory motion monitoring

Robin Navest[1], Cornelis van den Berg[1], Jan Lagendijk[1], and Anna Andreychenko[1]
[1]*Imaging Division, UMC Utrecht, Utrecht, Netherlands*

Purpose: Respiration often leads to artifacts in human torso MR images. To avoid these motion artifacts, triggered or gated MR acquisitions are performed and a reliable motion sensor is a necessity. Usually, this sensor is an extra device placed on the patient (i.e. pneumatic belt) or an additional MR acquisition (i.e. MR navigator), which itself can induce artifacts in MR images [1]. It has been shown that thermal noise variance of the receive RF coil can effectively pick up respiratory motion [2] and, therefore can potentially replace existing motion sensors in MRI. However, to extract the respiration from the thermal noise variance fluctuations, the latter has to be filtered first which can lead to a time delay. In this study, a predictive filter was designed and tested. This filter predicts the respiration phase for each acquired k-line based on the thermal noise of a local receiver array.

Methods: Free breathing experiments on six healthy volunteers were performed on clinical MR scanners. Three different groups were defined: 1.5T with a 16 channel receive body array (3 volunteers), 3T with a 16 channel array (2 vol.) and 3T with a 32 channel array (1 vol.). Both receive arrays consist of overlapping loop coils. Noise samples were acquired either by switching off the RF and gradients or from the noise only region of 2D balanced gradient recalled echo (GRE) sequence (cine MRI frames). To ensure a sufficient amount of noise samples in the latter case, the FOV was extended in read-out direction, which resulted in a maximum sampling rate. Cine MR frames were collected in sagittal, coronal and transversal slice orientation with a flip angle of 50º, TE=1.5/1.9 ms, TR=3.1/3.9 ms, number of collected points per TR: 672/688 at 1.5/3T respectively. Per coil the measured signal was normalized to its median and a correction for the difference in receive bandwidth between measurements was implemented. The respiratory belt signal was also recorded and served as an external respiratory reference. However, the respiratory belt is only a qualitative measure.

To extract respiration from the thermal noise variance fluctuations without time delay a Kalman filter [3] was applied to a weighted combination of all receive coils. The weights were taken from the first principal component after the principal component analysis [4] in coil dimension. The Kalman filter uses a squared sine wave model with variable frequency and amplitude to predict the next respiration phase. To achieve optimal results a 10 second training period at the beginning of each measurement is used to estimate initial values of the Kalman filter parameters (i.e. the uncertainty of the measurement, frequency and amplitude of respiration) and calculate the coil weights.

The modulation depth was calculated as a measure to compare the results of different volunteers and is defined as three times the standard deviation. To assess the performance of the Kalman filter the results were compared to the moving average filter (length 2 s) by calculating the normalized difference between them. The difference in mean modulation depth between the different field strengths and receive arrays was checked using a t-test.

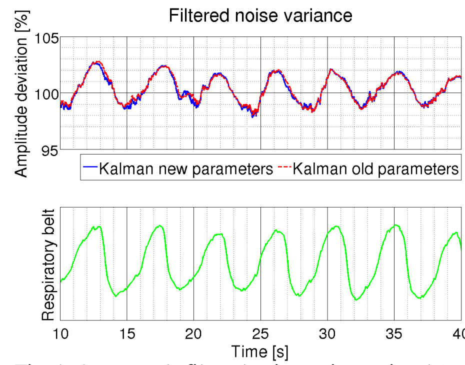

Fig. 1: An example filtered noise variance signal (upper graph) and the corresponding respiratory belt signal (lower graph). The Kalman filter was applied using initial parameters calculated from this measurement (blue solid line) and from an identical measurement performed 30 minutes earlier (red dashed line). This resulted in a negligible difference.

Results and discussion: The filtered noise variance signals show a periodic modulation similar to the respiratory belt (Fig. 1). Two identical measurements were performed 30 minutes apart, to show the influence of the initial Kalman parameter estimation on the resulting respiration signal. Applying the Kalman filter on the second measurement with parameters calculated from the first (red) and second (blue) measurement (Fig. 1) resulted in a 0.21% difference.

None of the three groups had a significantly different mean modulation depth (lowest p-value=0.83) between noise only and balanced GRE MR images (Fig. 2). This proves the noise source is the same with and without MR acquisition. The modulation depths differed between receive arrays and field strengths (Fig. 3). The measured mean modulation depth is significantly higher (p-value=0.0029) at 3T (3.0±0.93%) than at 1.5T (1.9±0.95%) for a 16 channel body array. This can be explained by the fact that the resistance of a coil scales with frequency [5]. For the 32 channel body array at 3T the modulation depth is 13.8±1.3%. The 32 channel receive array has a significantly higher mean modulation depth compared to the 16 channel array at 3T (p-value<0.0001). This is most likely caused by the different coil size of both receive arrays.

The difference between the results of the Kalman and moving average filter was 0.79±0.33% at 1.5T, 0.55±0.17% and 1±0.15% at 3T for the 16 and 32 channel receive array respectively. This small residual is caused by higher frequency fluctuations on top of the respiration extracted by the Kalman filter. To decrease these higher frequency fluctuations a recursive first-order low-pass filter will be merged into the Kalman filter in the future.

Conclusion: Respiration phase can be predicted real-life per k-line without time delay using thermal noise variance of the receive arrays within clinical 1.5/3T MR systems. The navigator also works real-time, however it always has a time delay because of the extra MR acquisition. Furthermore, the filter shown here is universal and can be applied to monitor respiratory motion with or without actual MR acquisition. The real time applications such as motion predictions or tracking are a major advantage of the Kalman filter with respect to retrospective filters (e.g. moving average). Possible applications are MR guided treatments (e.g. MR linac, HIFU) and hybrid MR systems (e.g. PET-MRI). Moreover, when the receive array is kept in place this method could be used in sequential systems.

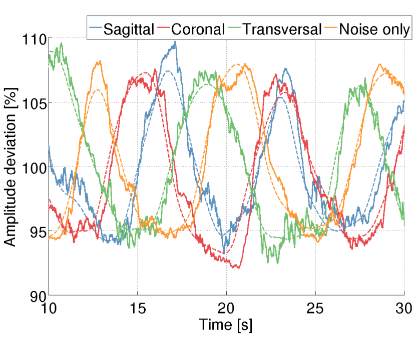

Fig. 2: An example filtered thermal noise variance of sagittal (blue), coronal (red) and transversal (green) GRE MR image slice orientation and noise only (orange) by Kalman (solid) and moving average (dashed) filtering. Modulation depth is the same for all four cases.

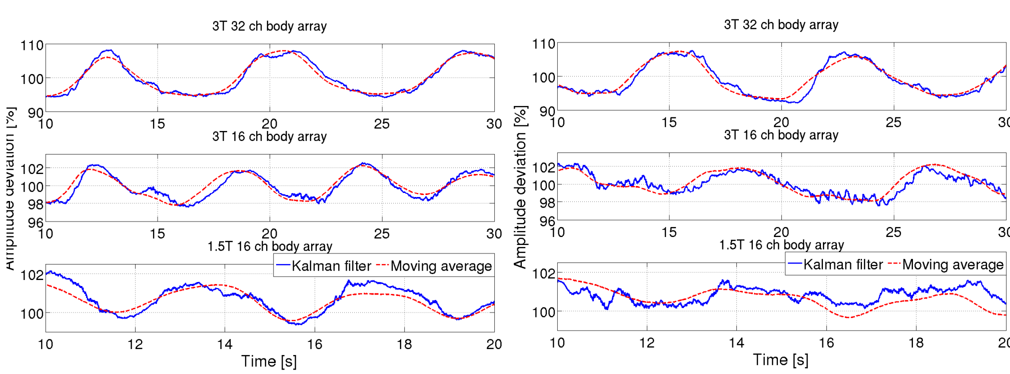

Fig. 3: Noise only (left) and a coronal (right) GRE measurement filtered by Kalman (blue solid line) and moving average (red dashed line) for each of the three groups. For visibility only 2.5 breaths are shown and sagittal and transversal slice orientation were left out. Notice the modulation depth differs between receive arrays and field strengths.

References: [1] Nehrke K, et al. (1999) MRI 17:1173-81; [2] Andreychenko A, et al. (2013) ISMRM 21:92; [3] Welch G, et al. An Introduction to the Kalman Filter (1998); [4] Jolliffe I. Principal component analysis (2005); [5] Edelstein WA, et al. (1986) J Magn Reson. 125(1):65-71.