Intrinsic Detection of Corrupted Data

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INTRODUCTION

In most MR images, data from adjacent lines in K-Space exhibit at least some degree of correlation between them. These correlations can arise from the object geometry, imaging parameters such as an extended field of view or by coil sensitivities in multi-channel acquisitions. It has been shown that in a 2D segmented sequence these correlations can be used to detect and correct in-plane rigid body translation between segments (1). This work extends this idea to show that correlations between adjacent segmented K-Space lines can also be used to detect non-rigid body motion or motion that occurs out of plane. As a result, some segmented sequences have a built in ability to detect corrupted data.

THEORY

Consider the cross correlation between two adjacent sets of equally spaced K-Space lines. The cross correlation function in image space is (1):

$$c(x,y)=\sum_{j=0}^{N-1} N_e e^{i\pi\left(\frac{2L}{N}+N-1\right)j}\,\delta\left(x-x_l,\,y-y_l-jN_e\Delta y\right)\otimes\Im\left(e^{i\phi_{ERROR}}\right) \qquad [1]$$

where N_e is the number of acquisition lines in a segment (echotrain length in a turbo spin echo sequence), N is the total number of segments (echotrains) required to fully sample K-Space, Δy is the spacing between voxels in the phase encoding direction and (x_l,y_l) is the bulk translation of the object (if any) between the L and L+1 segments (echotrains). Basically Eqn. [1] represents a set of equally spaced delta functions convolved with an error function, $\Im(\exp[i\bullet\phi_{ERROR}])$. The error function is due to correlation errors between adjacent sets of lines. These errors are present even when there is no motion of any kind. In the case of no motion, the error function is more sharply peaked. As the amount of data corruption increases, the error function becomes more spread out (Figure 1). As a result, a measure of the relative sharpness of the error function in Eqn. [1] provides a measure of data corruption.

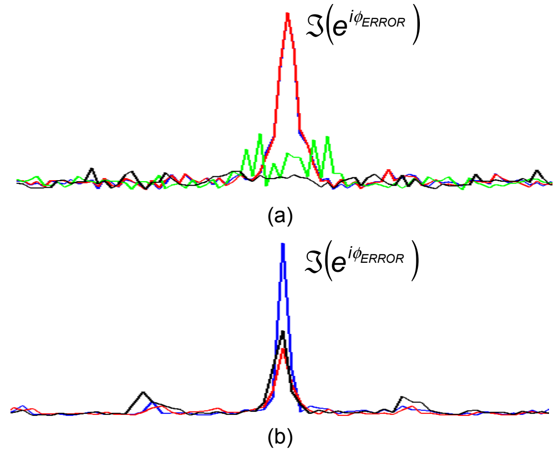

Figure 1. Typical error functions from a head image with translation and rotation is shown in (a). The red line corresponds to no motion, the blue line corresponds to a translation of about 5 pixels, the green and black lines correspond to a rotation of about 1° and 5° respectively. The error functions from real volunteer neck data with swallowing and nodding is shown in (b). The blue corresponds to no motion, the black line corresponds to swallowing and the red line corresponds to head nodding.

METHODS

Three sets of 2D Turbo Spin Echo (TSE) images were acquired from a cooperative volunteer on a Siemens Trio 3T scanner. No gating of any type is used. In the first set the volunteers head was restrained to minimize motion and no swallowing was noted. During the second set of images the volunteer was asked to swallow during a selected echotrain. In the final set, the volunteer was asked to nod their head during a selected echotrain. The error function was estimated by considering one of the delta function peaks in Eqn. [1]. The sharpness of the error function was measured with a weighted sum that varies inversely with the distance from the peaks center.

DISCUSSION

Figure 1 shows that the phase error function is an effective measure of some common types of data corruption. For rigid-body translations the error function does not respond noticeably (Red line in Fig. 1a), however, the shift of the delta functions in Eqn. [1] allows for this type of motion to be quantified. For rigid-body rotations, even small rotations can cause significant broadening of the error function (Green/Black lines in Fig. 1a). Non-rigid body motion, such as swallowing in this case, is also seen to broaden the error function (Black line in Fig. 1b). Asking a volunteer to nod their head will cause through plane motion and consequently caused a broadening of the error function as well (Red line in Fig. 1b). Figure 2 shows the detection of corrupted data from a real volunteer data set. The red line represents a data set where the volunteer was prompted to swallow during the acquisition of the 16th echotrain of a TSE sequence. The blue line represents a data set where the volunteer was asked to nod their head during the acquisition of the 27th echotrain. There is an obvious peak in both cases to indicate the corrupted data (Fig. 2). Because the corrupted data is compared with both the previous and following adjacent segments, it results in two consecutive peak values for each line. This makes the assumption that the object had corrupted data for a single segment and then returned to being relatively motion free for the following segment. These types of assumptions get more complex as the motion becomes more frequent and only need to be made if the data is analyzed post acquisition. A better solution is to monitor data as it is acquired and reacquire the corrupted data shortly after detection. Therefore, no assumptions need to be made about when the motion started or stopped.

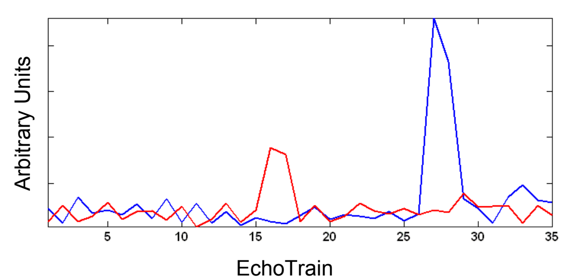

Figure 2. Measure of the error function broadness for two different 2D TSE data sets from the neck. The red line shows swallowing during the 16th echotrain while the blue line shows the volunteer nodding during the 27th echotrain. Because the corrupted data is compared with both the previous and following adjacent segments, it results in two consecutive peak values for each line. Hence the red line has a peak at the 16th and 17th echotrains, but only represents motion during one echotrain (the 16th).

CONCLUSION

As in most cases, more patient testing should be completed to validate the robustness of the technique, but the simulated and real data acquired to date show that monitoring the error function in Eqn. [1] to be an effective way to detect corrupted data segments.

REFEREENCES

1. Mendes et. al., MRM 2009;61:739-747