Data Rejection Schemes, Autofocus & Quality Metrics

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Introduction

K-space is filled as a function of time during acquisition. The image is the Fourier Transform (FT) of this k-space and inconsistencies in k-space due to motion manifest as blurring and ghosting in the image. If the errors in k-space are regarded as a modulation that multiplies the true k-space, then the effect on the image is a convolution of the true image with the FT of this modulation (the Fourier convolution theorem). This means that to some extent the pattern of ghosting seen in the image tells us about the source of the artefact [1, 2]. For example, pulsatile flow in a vessel passing through a slice often leads to periodic ghosts. Few motion correction schemes try to determine motion directly from the pattern of image artefacts, but the concepts of ghosting and inconsistencies of k-space are useful for the understanding of motion correction techniques.

The convolution theorem also applies in the other direction when multiple coils are used as receivers. The sensitivity of each coil multiplies the underlying object, resulting in a convolution of k-space with the FT of the sensitivity profile. A consequence is that k-space lines are linked to neighbouring lines and this can be used to check data consistency or estimate a corruption due to motion.

Data Rejection

Prospective

If damaged data is to be avoided or rejected (rather than corrected), then it has to be identified and the missing portions of k-space either re-acquired, or a reconstruction used that can cope with missing data. The triggering and gating of respiratory or cardiac acquisitions routinely use ECGs, respiratory sensors or pencil beam navigators to identify less favourable phases of the respiratory or cardiac cycles. Single profile navigators have been correlated with a reference to decide upon rejection [3]. In multi-shot DWI where tiny pulsatile motions during the diffusion weighting period cause large image phase errors, motion corruption can be detected using 2D navigators. In [4], the width of the central k-space peak for each 2D navigator was analysed and where peaks were broadened by image phase errors, the corresponding shots were rejected and re-acquired before the end of the scan. Prospective rejection has the advantage that re-acquisition can be efficiently targeted to data that needs to be re-acquired, however, processing needs to be on-the-fly. Prospective analysis takes place during acquisition, before the complete dataset is available, so methods based on consistencies of the whole data are difficult to apply prospectively.

Retrospective

In order to identify portions of k-space to reject, there needs to be a comparison of the k-space either with k-space from another measurement, or computed from the existing data using some form of prior knowledge. As mentioned, known coil sensitivities can be used to generate k-space from neighbouring lines for subsequent comparison. Alternatively, k-space can be generated by non-linear manipulations of the image, for example enforcing a known region of support or edge enhancement. Various combinations of these concepts have been used for motion detection and correction [5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15].

Rather than apply a binary accept/reject decision, data can be weighted during reconstruction. Weights that are comparable across an acquisition can be generated using sequences that have inherent self-navigation, e.g. [16, 17]. Gating normally uses a measured signal but for fetal cardiac imaging this is difficult and a parameterisation of the heart rate has been used with an entropy-based assessment of image quality to determine the correct cardiac timings [18]. The cost function in this metric optimised gating scheme is similar to that used in autofocus motion correction methods.

Autofocus

Autofocus techniques aim to iteratively determine and correct for the motion that took place during a scan [19, 20, 21, 22, 23]. The motion is found as part of an optimisation process that minimizes a cost function. The ideal cost function should be at a minimum when the image is free of motion artefacts.

Motion that is affine in the image domain has a known analytic description in k-space [24]. (This is a consequence of both the Fourier Transform and affine motion being linear operations. Translations become phase ramps and rotations are rotations about the same angle.) Cost functions are discussed in the next section and here we focus on the optimisation scheme.

Autofocus optimisation schemes have predominately been somewhat ad hoc, designed for specific types of sequences and expected motion. Fundamentally the cost function minimisation is a difficult problem because of the large number of unknowns and presence of local minima. The number of unknowns is related to how finely we discretise the acquisition time and the number of parameters used to describe the motion. For example, a spin echo sequence with time discretised to the acquisition time of each of 256 phase encode lines, and motion assumed to be rigid in-plane (two translation directions and one rotation angle), would have $256 \times 3 = 768$ unknowns.

The phase change to a single line of k-space due to translations in the phase encode direction is periodic meaning that there are multiple values of phase encode translation that will give the same value for a cost function, leading to local minima. The period of this translation decreases for k-space lines further from k-space centre, corresponding to only small displacements for lines acquired near the edge of k-space. To compound the difficulties near the edges of k-space, the signal to noise ratio in that region is poor.

One strategy to reduce these noise and periodicity problems is to consider multiple phase encode lines to have experienced the same transformation. This corresponds to a temporal grouping of lines. The problems of variable SNR and oscillations in cost functions can be reduced by acquisition schemes that acquire k-space in interleaved shots. In this case, each shot includes lines from central and edge regions of k-space.

Conceptually, one should use any appropriate information that is available to reduce the dimensionality or ranges of iterative searches. When alternative measures of motion are available, even if they are not direct measurements, they can be used to constrain the autofocus search (sometimes also permitting determination of motion that is only locally rigid) [25, 26, 27]. Taking an alternative view-point, autofocus can be used to 'tidy-up' other corrections, for example to correct for calibration errors in tracking equipment [28].

Many optimisation schemes cycle around a set of trial transformation parameters accepting values that minimise a cost function without the need to calculate the gradient of the cost function. If the trial steps cover a reasonable range, some local minima may be avoided but the lack of derivative information can lead to slow searches. In the case of the gradient entropy cost function, an analytic derivative for small rigid motions has been derived and used for rapid autofocussing [23].

One further point to note is the reference position. If we do not 'anchor' the motion and allow the optimisation to find a transformation at every time point, the average position is not fixed because most cost functions are invariant to a rigid displacement. In practice the reference position will be determined by the average position of the subject throughout the scan, weighted towards their position when the centre of k-space was acquired (where the energy is highest). One can reduce the number of unknowns by not searching for transformations at one time point, effectively making this the reference position. Whilst this has the advantage of reducing the number of unknowns, it can make the cost function minimisation harder because it forces the motion to be at the non-fixed time points.

Cost Functions and Quality Metrics

Autofocus algorithms require a cost function that is a minimum when the motion artefacts in an image are at a minimum. In general, a cost function is an attempt to quantify our prior expectations about the properties of an artefact-free image. No single measure is universally adopted and this is linked to the related difficulty of assessing image quality following most new reconstruction algorithms. (Note that the cost function in an autofocus optimisation may include both an image quality term, and regularisation terms to constrain the solution [29]).

The final application of MR imaging is usually in radiological reporting where tissue contrast, artefacts and resolution can affect the diagnostic value in different ways, depending upon context. Radiologist scoring is widely accepted in clinical journals although it is subjective and there is no universal scoring system for image quality, though standardisation efforts such as the BI-RADS scheme for breast reporting, may be applied to image quality in the future. When scoring is performed by more than one radiologist, quantities such as the Intra Class Correlation Coefficient may be used to quantify the variability between observers.

As part of an iterative process such as autofocus, mathematical cost functions are required. In part, the expressions for these cost functions have been inspired by work in radar, optics, astronomy, image compression and visual perception. In MR autofocus, assessment is almost always performed in the image domain because there is no clear structure to k-space. The repeated Fourier Transforms required after each trial motion correction of a portion of k-space are one of the factors that cause autofocus algorithms to be slow. Note that where a cost function is comparing to pre-existing data, for example from a training set, it could be performed on k-space without FT. Comparisons to training data can also be applied in the image domain to images that are aliased due to undersampling, e.g. [30].

Image entropy has been widely used and this is underpinned by the observation that entropy tends to increase when motion ghosts spill out into image regions that should be dark. Note that in MR autofocus, entropy is often calculated using the pixel intensities themselves, but it may also be computed from the frequencies of an image histogram. In a comparison of many cost functions [31], the gradient entropy was preferred and this has also become a popular metric with the advantage of an analytic approximation to the derivative [23].

Prior expectations about the rank and sparsity properties of data have recently been used in motion alignment [32] and one could envisage other metrics based on the sparsifying transforms used in compressed sensing or the expected Hermitian symmetry of k-space being applied to motion correction.

Conclusion

The uptake of autofocus-type algorithms has been slow, perhaps due to factors such as long algorithm times, uncertainties in reliability (though quality rarely degrades), sequence-specific algorithms, motion often restricted to rigid 2D, and, a requirement for access to the complex raw data with associated coil sensitivity profiles, scanner phase corrections and timing information.

Ongoing work is addressing many of these issues. The long-term solutions are likely to use an appropriate mix of prior knowledge, information from other measures and algorithmic methods more commonly used in the optimisation community. We look forward to further improvements and to studies quantifying accuracy and clinical benefit.

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