CORRELATIVE AVERAGING FOR RADIAL MAGNETIC RESONANCE IMAGING

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Abstract

Although Magnetic Resonance Imaging (MRI) has faced a dramatic increase in real-time capabilities over the last year, acceptable image quality still limits the actually achievable acquisition speed. This paper presents a motion-compensated noise filter that, on the basis of hierarchical motion estimation and edge-preserving adaptive weighted averaging, has been integrated into a segmented radial MR acquisition scheme. In several studies of moving joints, the proposed approach led to significant reductions in the noise level without introducing motion blur. The improved image quality would, in principle, allow more than double the acquisition speed, retaining the original image quality.

Keywords: image processing, Magnetic Resonance Imaging, motion compensated filtering, radial acquisition.

1. Introduction

Over the last years, Magnetic Resonance Imaging (MRI) has shown rapidly growing capabilities for real-time applications. However, the application of fast pulse sequences is still limited by the signal-to-noise ratio of the signals acquired, and the acceptable image quality often limits the actual acquisition speed. In contrast, slower acquisition speed leads to stronger motion artifacts. Therefore, a compromise between overall image quality and acquisition speed has to be made.

In this paper, we propose an approach to exploit correlations between successive frames of MR movie sequences to remove noise without introducing motion blur ('Correlative Averaging'). Noise removal subjects the originally measured signals to linear or non-linear low-pass filters. Filtering individual frames of a movie sequence independently of each other (two-dimensional
filtering) does not exploit the full potential for noise removal as it does not make use of the temporal correlation of intensity values between successive frames to achieve better noise suppression on the basis of larger data volumes. In contrast, straightforward application of a three-dimensional noise-removal to the movie sequence leads to unwanted motion blurring. Compensating for the movement of the objects imaged turns the movie into a ‘quasi-static’ three-dimensional data set that can be subjected to three-dimensional noise-removal without motion blurring. This is the basic idea of ‘Correlative Averaging’ — noise-robust motion estimation with motion-compensated low-pass filtering [1].

The hierarchical technique investigated in this paper lends itself well for direct integration into radial MR data acquisition schemes. Segmented k-space sampling with integrated motion estimation has been used in conjunction with motion-compensated adaptively weighted average (AWA) filtering. In order to avoid any spatial blurring induced by the filter, only pure temporal filters are examined. This paper describes the approach and presents first results of this novel technique.

2. Motion estimation

Motion estimation is based on the model of ‘Optical Flow’ originally defined by Horn and Schunk in 1981 as ‘... the distribution of apparent velocities of movement of brightness patterns in an image’ [2]. Assuming that brightness changes in an image are only caused by movement of the object imaged, the object brightness remains constant along the object path. The most widely used techniques for following constant brightness patterns and thus reconstructing the object path are based on what are usually called block-matching algorithms. These methods take a rectangular block of neighbouring picture elements in one image and, in a second image, try to locate, with respect to some similarity measure, an equally sized block that optimally matches the intensity values of the first block. For the MR-applications described in this paper, we maximized double correlation to identify most similar block positions. The differences in the respective block positions directly give the displacement of the imaged object part from the first to the second image. Numerous versions of block matching have been proposed (for an overview of this extensive topic see for example [3] and the literature referenced therein), and hardware implementations for motion estimation at TV-rate have become available [4]. The basic assumptions underlying these approaches are:

(i) changes in brightness are due to motion only;

This is an assumption that is not always fulfilled in MR applications due
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to the appearance/disappearance of motion artifacts, to global contrast changes between successive movie frames, and in particular to motion perpendicular to the image plane.

(ii) no deformations inside a block;
To locate the most similar block in the second image, only shifts are taken into account to keep the computational complexity within practical limits. This means, however, that no deformations such as rotations or elastic distortions of the underlying-image object may occur over the extent of a block. To a certain extent, this can be controlled by selecting a proper block size — the stronger the non-linear distortions, the smaller the block size required to keep elastic deformations within the pixel resolution over the block extent. However, there is a lower limit to a block size. The smaller the block, the more locating similar blocks in the second image becomes ambiguous because of noise and, to a less significant degree, brightness structures to match.

(iii) corresponding brightness patterns can be uniquely identified;
This assumption is somewhat related to the previous ones. It excludes periodic (fortunately unlikely in MR applications) structures and puts an upper limit to the corruption by noise as well as a lower limit to the significance of the brightness structures inside the block boundaries. To a certain extent, these limits can be met by selecting sufficiently large block sizes.

Whenever movements of organs in the human body result in spatially smooth displacement fields, these can be reliably estimated even under bad signal-to-noise conditions by hierarchical block matching [5] using sets of images of decreasing spatial resolution that are derived from a full-resolution image (Fig. 1). In its simplest form, the spatial resolution is reduced by averaging $2 \times 2$ neighbouring pixels on one level averaged into one pixel of the next lower-resolution level. Starting from the lowest-resolution level, motion estimates are progressively refined by taking the displacement obtained at one level as the starting position for a local optimization at the next finer level to arrive at a more accurate update. This top-down refinement ends at the original resolution level and provides a full-resolution displacement estimate. This approach is very fast as, because of the reduction in geometric scale, it only involves small search areas and block sizes for detecting even large displacements. It produces smooth displacement fields reflecting true physical movements and is robust against noise and motion artifacts as only the largest and best-defined object structures survive up to the lowest-resolution level where the estimator starts. This approach is well suited for orthopedic applications such as motion studies of joints and ligaments.
Fig. 1. Three-level image pyramid erected over a 256 x 256 radial MR image of the moving knee.

3. Integration of motion-estimation into radial MRI

The hierarchical approach to motion estimation can be directly integrated into segmented radial MR-acquisition schemes [6]. In order to follow a dynamic process, data are continuously acquired along radial lines in k-space and image reconstruction is done by conventional filtered back-projection. In Fig. 2, two radial MR-acquisition schemes are depicted. Figure 2a shows a linear acquisition using a small angular increment $\delta \theta$ similar to the acquisition process known from CT. In Fig. 2b, the angular increment $\delta \theta$ of succeeding projections is increased providing for a faster but coarser k-space at low angular resolution. Even a coarse segment already covers the central part of k-space sufficiently densely to allow for the reconstruction of a low-resolution image. Subsequently acquired segments are interleaved with previously acquired ones to increase the angular resolution until the whole k-space is filled and a high-resolution image can be reconstructed. In detail, the
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Fig. 2. In a linear acquisition scheme (a), data are successively acquired on radial lines in $k$-space using a small angular increment $\delta \theta$. In a segmented radial acquisition scheme (b), a larger increment $\delta \theta$ provides a faster but coarser coverage of $k$-space. After $n = 2\pi / \delta \theta$ projections, a segment is acquired.

The acquisition process consists of the following steps:

(i) After the acquisition of one data segment, an image with the lowest resolution can be reconstructed using the central part of $k$-space.

(ii) After the acquisition of three data segments, an image at the second resolution level can be reconstructed. Therefore, two data segments have to be combined. In order to provide a homogeneous distribution in $k$-space the segments 1 and 3 are combined.

(iii) After acquisition of four segments, a high-resolution image can be reconstructed using all segments which ensures that the Nyquist-theorem is fulfilled in the whole $k$-space.

Figure 3 illustrates the reconstruction of $64 \times 64$, $128 \times 128$, and $256 \times 256$ images from four successively acquired data segments. It is visible that the images with a smaller numerical resolution have a higher signal-to-noise ratio (SNR). Theoretically, the SNR increases by a factor of $4/\sqrt{2}$ if the resolution is decreased by a factor of two.

The reconstruction of images at different resolution levels can support the concept of hierarchical motion estimation introduced in the previous section. With four segments having been measured (Fig. 3), it is already possible to reconstruct images at three resolution levels. The acquisition of the fifth segment provides the reconstruction of a low-resolution image at a different motion state. At this point of time, a coarse motion estimation can be carried out using the low-resolution images reconstructed from segment 1 and 5. As mentioned earlier, these images have a relatively high SNR leading to a noise robust estimation of displacement vectors. In parallel, segments 6 and 7 are measured which provides the reconstruction of an image at the second resolution level. Hierarchical motion estimation can continue at this resolution, in
Fig. 3. Hierarchical motion estimation. The combination of data segments offers the possibility of a multi-resolution reconstruction. An image at resolution level 1 can be reconstructed from the central data of one segment. An image at resolution level 2 can be reconstructed by combining two data segments. A high-resolution image can be reconstructed using all data segments. Images at different resolution levels can support the concept of hierarchical motion estimation.

In particular the coarse displacement vectors obtained from the low-resolution images are used as start positions for a local search on images at the second resolution level. Meanwhile, segment 8 is acquired and a high-resolution image can be reconstructed using segments 5 to 8. The displacement field can thus be refined using both high-resolution images. After the next segment is acquired the described process can start again.

In Fig. 4 motion fields at the different hierarchy levels are shown in the case of a moving knee. The arrows represent the displacements for each block, indicating that the lower limb is swinging to the left. The displacement vectors are refined going from one level to the next because smaller block sizes are used.
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Fig. 4. Motion fields of a moving knee using hierarchical motion estimation. The arrows represent the displacements for each block. (a) The displacement vectors estimated on the coarsest level. (b) The refined motion field at the intermediate resolution level. (c) The motion field at the target resolution. The resulting displacement field smoothly extends beyond physical object boundaries, such as the skin surface. The reason for this effect lies in the limited refinement of the displacement vectors between adjacent resolution levels.

The resulting motion field is continuous in space and can be used to compensate for motion between two images.

4. Motion-compensated filtering

Correction for object motion between successive frames turns a sequence of images of a moving object into a 'quasi-static' three-dimensional data set that can be subjected to three-dimensional filtering. It is important to preserve edges along the time axis to avoid motion blur from incorrect motion estimates. This 'fault tolerant' filtering is necessary as fast and error-free motion estimates are nearly impossible, especially for our target applications. Several filters have been designed for noise removal in image sequences with or without motion-compensation [7–10]. A very efficient adaptive weighted averaging (AWA) filter has been proposed in Ref [11] that controls the weighting coefficients of simple averaging inversely to the local gray value gradients $\nabla G$

$$w \approx \frac{1}{1 + \alpha \cdot \max(\sigma^2, |\nabla G|^2)}$$

Large gray value gradients lead to small weighting coefficients and thus exclude picture elements across steep gray value edges from filtering. This automatically controls the trade-off between improved signal-to-noise properties and better delineation of object details. The behaviour of this filter is controlled by two parameters. Gray value differences smaller than $\sigma^2$ are not...
taken into account, i.e. \( \sigma^2 \) separates significant edges worth being preserved from insignificant edges that are normally produced by noise and should be low-pass filters — \( \sigma \) is thus determined by the noise level in the image data. The parameter \( \alpha \) controls the edge-preserving effect, the larger \( \alpha \) the stronger the averaging is controlled by local gray value differences.

This filter can be applied along the time axis alone (temporal filter) or it may also include the spatial domain (spatio–temporal filter). In the two spatial dimensions, the filter preserves edges delineating structures in the object images and thus leads to better conspicuity of anatomical detail in the filtered images. Along the time axis, the filter preserves pseudo-edges resulting from inaccurate motion estimates and avoids unwanted motion blur in the filtered images. This ‘fault tolerant’ filtering is necessary as truly accurate motion estimates are nearly impossible to achieve especially for our target applications. Brightness structures may be corrupted by noise and the assumption of ‘optical flow’ is likely to be violated. Changes of the image plane lead to the appearance/disappearance of image objects. In this way, edge-preserving averaging automatically controls the trade-off between improved signal-to-noise properties and better delineation of object details.

In this paper, only pure temporal filters with and without motion compensation are examined. In either case, three consecutive frames are used during the averaging process. Motion compensation is performed with respect to the central frame as alternating forward–backward motion estimation between successive frames results in more accurate displacement fields (Fig. 5).

The quantitative evaluation of the effect of ‘Correlative Averaging’ demands the estimation of local improvements in SNR as the AWA filter, by its adaptive nature, produces a spatially varying SNR. To simulate a real measurement, three successive frames (previous, current, and next) were taken from an MR-movie, and an ensemble of 256 frame triplets was created by adding Gaussian noise to the real and imaginary parts of the frame triplet of interest (Fig. 6). Each of these triplets was individually subjected to ‘Correlative Averaging’, and the standard deviations \( \sigma(x,y) \) and \( \sigma_I(x,y) \) over the ensemble were determined for every pixel before and after filtering. The improvement in SNR was taken as the ratio \( \text{SNR}_1(x,y) = \sigma(x,y)/\sigma_I(x,y) \).

5. Results

To estimate the quality of the motion estimation, difference images with and without motion-compensation are calculated (Fig. 7). The difference image without motion-compensation shows significant edges along moving objects parts that are not present, with respect to the noise level in the
Fig. 5. 'Correlative Averaging' process: for each frame a forward and backward motion estimation is carried out. The displacement fields are used to compensate for the motion between the frames. The quasi-static images are then averaged using an edge-preserving filter.

motion-compensated difference image. This is taken as an indication that motion has been estimated sufficiently accurately for the purpose of motion-compensated filtering.

Figure 8 compares an original image to the results of a pure temporal filter with and without motion-compensation. The results demonstrate that motion

Fig. 6. Evaluation of the improvement in SNR due to the filtering process. Gaussian noise is added several times to three consecutive images in order to create three consecutive image ensembles. The ensembles allow determination of the standard deviation along the ensemble axis for each pixel. Motion compensated filtering is applied to all ensemble images.
blurring can be avoided and a significant increase in SNR can be obtained if a motion compensation step is used prior to filtering. For a quantitative evaluation of the gain in SNR, an image ensemble was created by adding Gaussian noise whose standard deviation was set to 10% of the dynamic range of the original images.

Figure 9 shows gray-value coded improvements in SNR. The brighter the image, the better the improvement in SNR at that location. The use of the temporal AWA filter already significantly improves the SNR in non-moving or homogeneous parts of the objects, but leads to no or poor improvements along the edges of moving parts (dark edges in the left part of Fig. 9). These regions of poor SNR-improvement are much less pronounced in the resulting image obtained with a motion-compensated AWA filter (right-hand part of Fig. 9). In the background (region I of Fig. 9) the overall improvement of SNR was found to be 1.7, indicating that the corresponding values of three pixels

Fig. 8. Results of a pure temporal filter using three consecutive frames. The SNR in the original image (a) can be improved by using a temporal filter without (b) and with (c) motion compensation. Motion blurring effects are reduced using a motion-compensated filter (c).
Fig. 9. Evaluation of the improvement in SNR due to the filtering process. (a) Spatial distribution of the improvement in signal to noise for filtering without motion compensation. (b) Improvement in SNR in case of motion-compensated filtering. Region 1 contains background noise whereas bony structures are represented by region 2.

Fig. 10. 'Correlative Averaging' process: For each frame, two backward estimation $d_1$ and $d_{12}$ are needed to compensate the motion with respect to the current frame. When the displacement field $d_2$ is approximated by the concatenation of $d_{11}$ and $d_{12}$, only one backward motion estimation per frame is needed. The quasi-static images are then averaged using an edge-preserving filter.
were fully averaged. In the bony regions (region 2 of Fig. 9), the improvement in SNR has decreased to 1.5 because of imperfect motion compensation and the partial exclusion of pixel from averaging.

6. Conclusion

In the previous sections, it was shown how the concept of hierarchical motion estimation can be integrated into segmented radial MR acquisition protocols. Applying motion-compensated adaptive weighted filtering over three successive frames along the time axis, 1.5- to 1.7-fold improvements in SNR were obtained without introducing motion blur in the processed images. The improvement in SNR can either be used to increase image quality or to speed up the acquisition process, e.g. an improvement in SNR by a factor of 1.5 would allow a reduction in the measuring time by a factor of 2.25, preserving the original image quality.

Estimating motion with respect to the central frame of three successive frames is only applicable in a post-processing step, because a time lag of frame is needed to estimate motion forward in time which is not acceptable in real-time applications. For real-time MRI, motion has to be estimated from already acquired frames. Figure 10 shows such a 'Correlative Averaging' scheme. For each frame, motion is estimated from the last acquired frame to its two immediate predecessors. Sacrificing some accuracy in the motion estimates, this process can be further accelerated if motion is only estimated between immediately succeeding frames and by using concatenation of the respective displacement fields for extending the motion-compensated filter further into the past.

Due to the 'fault tolerance' of the AWA filter, 'Correlative Averaging' tolerates less accurate motion estimates. Sacrificing some SNR, this allows, in principle, motion-compensated filtering on only coarse motion fields that can be obtained much faster than the high-resolution displacement fields used so far, and this would open the door to real-time correlative averaging.

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Authors Biographies

Tobias Schäffter was born in 1967 in Berlin, Germany. He received his Master’s degree in Electrical Engineering from Berlin Technical University in 1993. He joined the Philips Research Laboratory Hamburg in 1993, where he worked as a PhD student on ultra-fast magnetic resonance spectroscopic imaging. In 1996 he received his PhD degree from Bremen University. Since 1996 he worked as a research scientist in the magnetic resonance group. His current interests include signal processing algorithms for a magnetic resonance fluoroscopy system.

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