Adaptive Threshold Masking

An Extended Bias Correction Algorithm for Heavily Biased MR Images

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Abstract. Image bias is a usual phenomenon in MR imaging when using surface coils. It complicates the interpretation as well as the algorithmic postprocessing of such data. We introduce a bias correction algorithm based on homomorphic unsharp masking (HUM) that is applicable on a broad range of image types (as long as fore- and background is separable), simple, fast and requires only minimal user interaction. The results of this new algorithm are superior to HUM, especially with regards to feature separability.

1 Introduction

MR images often suffer from inherent bias throughout the imaged intensity values. The development of specialized coils is an expensive method often not feasible for small animal research imaging, whereas the independent measurement of the bias field using phantoms is laborious and does not guarantee satisfying results. Therefore, we have to circumvent bias artifacts by means of image postprocessing. Our algorithm for bias correction is based on the homomorphic unsharp masking (HUM) [1] which needs very little user interaction – in contrast to e.g. interpolation methods [2] – and needs no specialized a priori knowledge and has less strict requirements on the imaged tissue than statistical bias correction methods [3]. HUM relies on low contrast background tissue and foreground features separable by threshold segmentation. It estimates the bias field by low-pass filtering the background tissue. In the case of rat brain MR angiograms the first requirement is fulfilled, but the separation of vessels from background tissue using only one threshold value is impossible due to the heavy bias. Therefore, we change HUM into an iterative algorithm that estimates the bias field and locally adapts the separation threshold to it alternately.

2 Methods

Our adaptive threshold masking (ATM) algorithm initially works almost identical to HUM. The user has to provide a threshold value indicating an intensity value above which a voxel is considered as foreground feature – in the case of angiograms: vessel – and will not be used for bias field estimation. Additionally a second threshold is provided that masks image background, i.e. out-of-body areas, which are not used for bias field estimation, either. Both threshold values are converted into threshold fields of the same size as the image data field, each threshold field voxel initially set to the corresponding threshold value. Then the algorithm performs following three steps iteratively:

1. Mask foreground and out-of-body background, i.e. every voxel with an intensity above the corresponding value in the foreground threshold field or an intensity below the corresponding value in the out-of-body background threshold field.
2. Create a bias field estimation by low-pass filtering the unmasked tissue. Effectively we use a cube-shaped kernel with uniform voxel weighting as low-pass filter. This can be efficiently implemented using floating average calculation along scan lines in each spatial direction subsequently, leading to a complexity of O(n) regardless of the kernel size.
3. Divide the threshold fields (not the image data!) by the bias field estimation.

Initially the ATM algorithm stopped the iteration when the distance of two subsequent threshold fields fell under a defined value. However, this makes it necessary to keep two copies of the threshold fields in memory. In conjunction with the image resolutions we use, this does not fit into the 3 GB process space of a usual 32 bit PC process, so we use a predefined fixed number of iterations instead. Usually 5 iterations are sufficient. The third iteration step is the crucial extension to the HUM algorithm. Initially in dark image areas the foreground is not masked correctly and thus the bias overestimated. However, by locally adapting the threshold to the bias field estimation it is lowered in these areas and leads to a better segmentation in the next iteration. The image data itself is corrected in a last post iteration loop step by dividing it by the last estimated bias field. If only one iteration is used, the threshold field adaption is never applied: effectively only iteration steps 1 and 2 are performed once, followed by the terminal image data correction, thus leading to the original HUM algorithm as special case of the ATM algorithm.

3 Results

Both HUM and ATM are profound bias correction algorithms that strongly improve the quality of biased images (Fig. 1). However, ATM has some advantages over HUM. Maximum intensity projections emphasize more vessels for ATM, in HUM the bias is still slightly visible and image features are clearly identifiable in the HUM bias field while the ATM bias field is much more independent of the features. Inspection of the histograms show a slightly more uniform intensity distribution after ATM correction compared to HUM. The run time of the ATM algorithm is less than a minute on a usual PC for a 512 voxels^3 data volume and allows several runs in order to achieve the best image quality.

4 Discussion

Adaptive Threshold Masking represents a simply, efficient and fast bias correction algorithm for any type of image that consists of foreground features, a

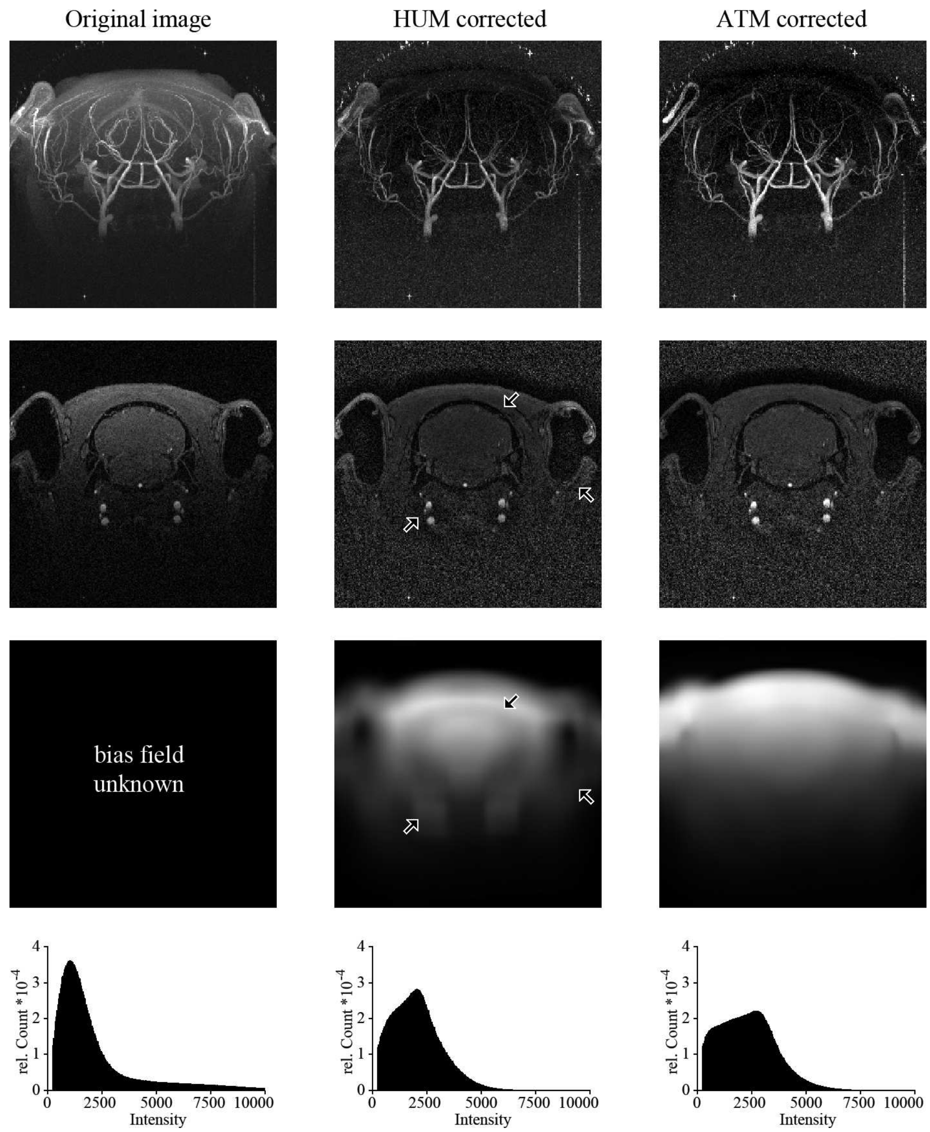

Fig. 1. From top to bottom: maximum intensity projection, exemplary image slice, bias field slice and histogram of the same image without bias correction, after Homomorphic Unsharp Masking and after Adaptive Threshold Masking. Arrows in HUM slices indicate features than are present in the bias field and indicate a faulty separation

low contrast background usable for bias field estimation by means of low-pass filtering and optionally an out-of-body background. It performs a robust and accurate bias field estimation, especially when the bias is so strong that image segmentation is impossible using only one global threshold value. We use ATM on a daily basis as a mandatory preprocessing step for automatic vascular system segmentation and reconstruction [4, 5]. This method strongly depends on possibly unbiased source angiograms and benefits much from the advantages of ATM over HUM, namely the better separability of background and foreground. Although ATM should be adequate for any type of image with the mentioned properties, so far we use it mainly for the bias correction of small animal cerebral vascular MR angiograms.

References

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