







# Registration of MRI and iUS Data to Compensate Brain Shift Using a Symmetric Block-Matching Based Approach

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**Abstract.** This paper describes the application of an established block-matching based registration approach to the CuRIOUS 2018 MICCAI registration challenge. Different variations of this method are compared to demonstrate possible results of a fully automatic and general approach. The results can be used as a reference, for example when evaluating the performance of methods that are specifically developed for ultrasound to MRI registration.

**Keywords:** Brain shift · Fully automatic · MRI · iUS  
Symmetric registration · Block-matching

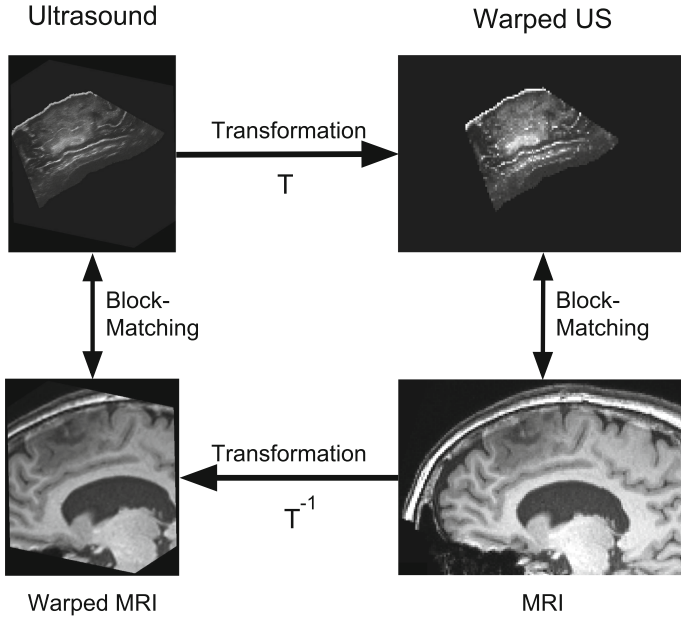
## 1 Introduction

Update of pre-surgical images and surgery plans to improve the accuracy of displayed information is an active field of research. Intra-operative ultrasound (iUS) is an accessible imaging technique that can be used to acquire data of the brain during a surgery. With these intra-operative images, the brain shift can be estimated via image registration. For the CuRIOUS 2018 MICCAI challenge, we suggest a method which uses a symmetric block-matching approach to fully automatically align the pre-operative MRI with the iUS image. This is an established method whose benefits were shown in different applications [2,3]. The results can then be compared to more specialized approaches in this field.

## 2 Methods

It has been shown that asymmetric registration algorithms can impair the evaluation of biomarkers, e.g. brain atrophy [9] and should thus be used with caution.

Direct comparison of an asymmetric and symmetric block-matching framework showed further advantages like improved capture range, higher accuracy and robustness of the symmetric approach [5]. The symmetric registration algorithm used in this comparison is published as part of the NiftyReg open source software package (version 1.5.58) [6] and is applied on this registration challenge (Fig. 1).



**Fig. 1.** Overview of the symmetric registration approach. In every registration step the iUS image is warped into the MRI space and vice versa. Block-matching is then performed in the respective domain to update the transformation with the established correspondences. The transformations are averaged to ensure inverse consistency.

## 2.1 Block-Matching Based Global Registration

The block-Matching method for registration iteratively establishes point correspondences between reference image and the warped floating image and then determines the transformation parameters by least trimmed squares (LTS) regression [7]. The LTS regression only considers 50% of inlier values.

For the block-matching, both images are divided into uniform blocks of 4 voxel edge length. The 25% of blocks with the highest variance of intensity values are used and the rest is discarded. Each of these reference image blocks is compared to all floating image blocks that overlap with at least one voxel (this results in a search space with 7 voxel edge length). The matching block for each

reference block is determined as the one with maximum absolute normalized cross correlation (NCC) according to

$$\text{NCC} = \frac{1}{N} \sum_{x \in b_r} \frac{[b_r(x) - \mu_{b_r}][b_f(x) - \mu_{b_f}]}{\sigma_{b_r} \sigma_{b_f}}, \quad (1)$$

with the blocks in reference ( $b_f$ ) and warped image ( $b_r$ ), the mean  $\mu$  and standard deviation  $\sigma$  within a block, and the number of voxel in a block  $N$ . To increase the robustness and decrease computation time, only a fraction of all blocks are matched.

## 2.2 Symmetric Registration Extension

The block matching step provides two sets of point-wise correspondences between the images: from image  $I$  to  $J$   $\{C_{I \rightarrow J}\}$  and vice versa  $\{C_{J \rightarrow I}\}$ . The second step is the update of transformation parameters via LTS regression. At every iteration  $i + 1$  and for both correspondences, the composition of the block-matching correspondence and the previous transformation  $T^{(i)}$  determines the new transformation by LTS:

$$T^{(i+1)} = \text{LTS}[C \circ T^{(i)}]. \quad (2)$$

To ensure inverse consistency (i.e.  $T_{I \rightarrow J} \equiv T_{J \rightarrow I}^{-1}$ ) at each update, the directional transformation matrices of the LTS regression are averaged according to [1]:

$$T_{I \rightarrow J}^{(i+1)} = \text{expm} \left( \frac{\logm \left( \text{LTS} \left[ T_{I \rightarrow J}^{(i)} \circ C_{I \rightarrow J} \right] \right) + \logm \left( \text{LTS} \left[ T_{J \rightarrow I}^{(i)} \circ C_{J \rightarrow I} \right]^{-1} \right)}{2} \right) \quad (3)$$

$$T_{J \rightarrow I}^{(i+1)} = \text{expm} \left( \frac{\logm \left( \text{LTS} \left[ T_{J \rightarrow I}^{(i)} \circ C_{J \rightarrow I} \right] \right) + \logm \left( \text{LTS} \left[ T_{I \rightarrow J}^{(i)} \circ C_{I \rightarrow J} \right]^{-1} \right)}{2} \right), \quad (4)$$

where expm and logm are the exponential and logarithmic matrix operators, respectively.

## 2.3 Experiments

The NiftyReg software is based on the NIfTI-1.1 file format so that the MINC files of the RESECT database [8] have to be converted first. We used the MINC tools provided by the McConnell Brain Imaging Centre, Montreal Neurological Institute at McGill University [4] for the conversion. The initial alignment of iUS and MRI images (based on tracking of the iUS probe) are derived from the header information. This alignment is the baseline and the corresponding results are referenced to as initial. Masks derived from thresholding the iUS image at an

intensity value of 0 (i.e. masking out the background) and dilating the result by 10 voxels are used for all registrations. Then the described block-matching based registration is applied with a 2 level pyramidal approach. On the first level, 10 iterations are computed, on the finer level only 5. The symmetric approach is evaluated once with the T1-weighted MRI (symm-T1) and once with the FLAIR MRI (symm-FLAIR). These approaches are compared to the four asymmetric approaches: with the iUS image as reference and the T1-MRI as floating image (asymm-US-T1) and vice-versa (asymm-T1-US) as well as with the iUS image as reference and the FLAIR-MRI as floating image (asymm-US-FLAIR) and vice-versa (asymm-FLAIR-US). These 6 approaches are each computed with a rigid and affine transformation. Furthermore the affine transformation that minimizes the target registration error (TRE) is included in the comparison as an optimal result (affine oracle).

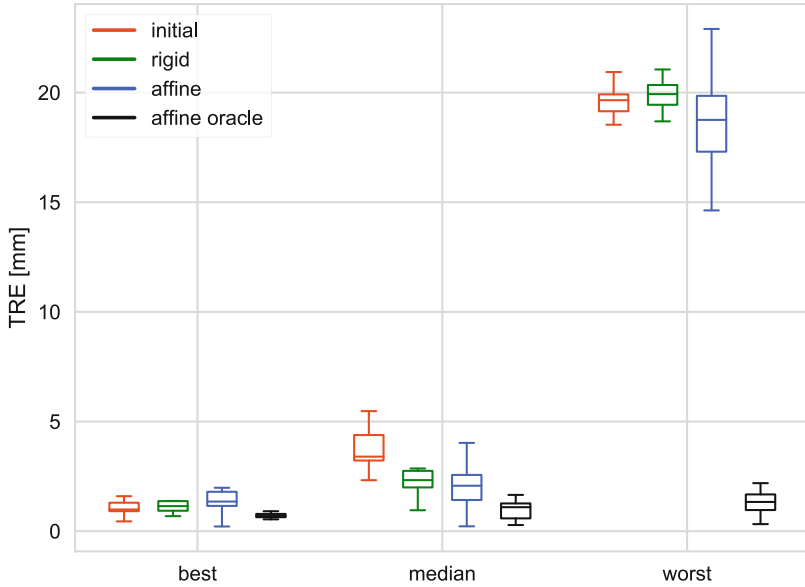
### 3 Results

For all described approaches, the average of all case specific mean TREs is computed as an overall measure of registration accuracy. The results are summarized in Table 1. It can be seen that the symmetric approach using the FLAIR data, symm-FLAIR, as well as the asymmetric approach asymm-T1-US fail and increase the TRE. The best approaches are asymm-US-FLAIR, asymm-US-T1 and symm-T1. The asymm-US-FLAIR approach shows the best results reducing the initial average TRE of 5.37 mm to 3.77 mm and 2.90 mm with rigid and affine registration respectively, improving 20 and 18 out of the 22 cases. For asymm-US-T1 the TRE is reduced to 4.34 mm and 3.78 mm, improving 15 and 17 out of the 22 cases with rigid and affine registration, respectively. The symm-T1 approach shows good results with an average TRE of 3.84 mm, on par with the asymm-US-T1 affine. This symmetric approach improved the TRE for 18 of 22 cases.

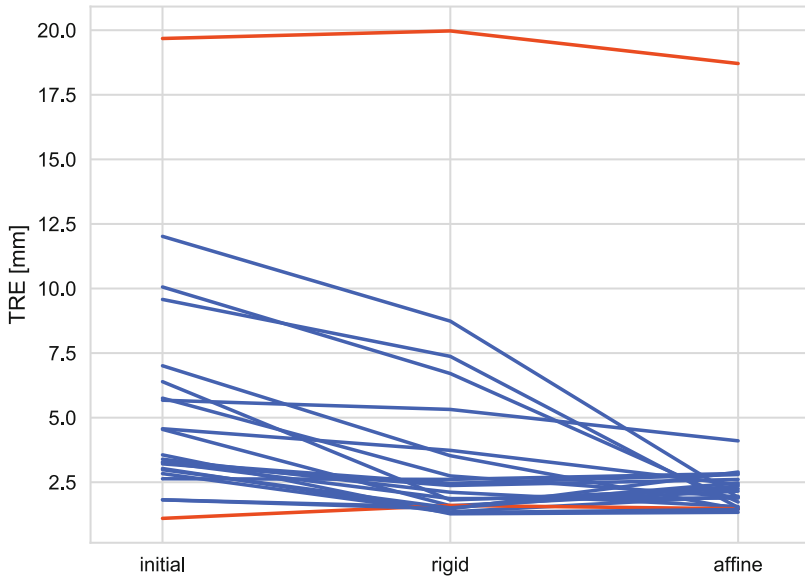
**Table 1.** Average mean TRE in mm and 95% confidence interval for all tested approaches.

	Initial	Rigid	Affine	Affine oracle
asymm-US-T1	5.37 [3.48, 7.27]	4.34 [2.71, 5.96]	3.78 [2.36, 5.19]	0.95 [0.88, 1.02]
asymm-T1-US		8.49 [6.41, 10.57]	16.15 [10.95, 21.36]	
symm-T1		3.84 [2.10, 5.57]	5.41 [4.48, 6.34]	
asymm-US-FLAIR		3.77 [1.91, 5.64]	2.90 [1.31, 4.49]	
asymm-FLAIR-US		8.84 [6.49, 11.18]	16.52 [11.52, 21.52]	
symm-FLAIR		8.75 [6.48, 11.02]	13.50 [9.05, 17.96]	

In a few cases, the initial alignment has rather large TREs which are not fully recovered by the approaches although the optimal computed transformation shows that an affine transformation is able to reduce the TRE to values similar to



**Fig. 2.** Boxplots showing TRE results for best-, median- and worst-case subjects of initial, asymm-US-FLAIR rigid, asymm-US-FLAIR affine, and affine oracle (from left to right within each group).



**Fig. 3.** Spaghetti-plot showing the mean TRE for every case with the initial position and the asymm-US-FLAIR approach with both rigid and affine registration. Blue lines indicate a decrease of the mean TRE by the rigid registration approach, red lines an increase. (Color figure online)

the other cases. Figure 2 visualizes the TRE distribution for 4 approaches (init, symm-T1 rig, symm-T1 aff, and opt) with 3 cases each: the best, the median and the worst case (determined by average mean TRE). Comparing the affine and the rigid approach, the affine increases the TRE on average and especially for cases with lower initial TRE. On the other hand, the TRE of the worst cases is reduced most by the affine approach. This can be seen in Fig. 3 where each line represents the mean TRE of an individual case. Most lines decrease from initial value to the rigid result before increasing to the affine result while the three cases with initial highest TRE decrease with the affine approach.

## 4 Discussion

We have demonstrated that a fully automated standard registration approach can reduce the average mean TRE of the given data set from 5.37 mm to 2.90 mm (using the asymmetric approach with the iUS image as reference and the FLAIR MRI image as floating image). One other asymmetric approach and a symmetric approach achieved acceptable results while the other considered approaches could not improve the registration accuracy. The given data set includes one outlier case with a very high initial TRE, which is not improved much in most approaches. Excluding this case yields even better results with 2.15 mm average mean TRE for asymm-US-FLAIR affine. These results require no user interaction and rely mostly on default parameters. Comparing the results to an optimal transformation based on matching the given landmark correspondences, it becomes clear that results could be improved further. Changes of, for example the similarity measure or pre-processing steps could be adapted for this registration problem. Furthermore the combination of the information of both MRI images into a multi-spectral registration approach could improve the results.

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