

# A Comparative Framework of Probabilistic Atlas Segmentation Method for Human Organ's MRI

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**Abstract** Recently, different image analysis methods are used for human body parts. But the internal pectoral muscle segmentation of important body parts in a automatic way is widely used. This is also vital for multi modal image registration. Previously, breast MRI image analysis by automatic pectoral muscle segmentation is studied. In this paper, we introduce a comparative framework of probabilistic atlas segmentation method for breast with brain, chest, heart and liver MRI. For breast, brain, heart and liver and chest segmentation, the obtained DSC values are  $0.76 \pm 0.12$ ,  $0.71 \pm 0.15$ ,  $0.66 \pm 0.08$ ,  $0.77 \pm 0.12$  and  $0.72 \pm 0.13$  respectively. The total overlap values for each case are  $0.76 \pm 0.12$ ,  $0.76 \pm 0.15$ ,  $0.71 \pm 0.08$ ,  $0.70 \pm 0.12$  and  $0.70 \pm 0.13$  respectively.

**Keywords** Multi atlas based segmentation • Breast MRI • Brain MRI • Heart MRI • Liver MRI • Chest MRI

## 1 Introduction

The MRI of the important body parts is a technique which is used to detect the cancer disease tumor detection of patients. It needs to perform automatic analysis of breast, brain, liver, heart and chest MRI image analysis. Gubern et al. [1] developed

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a method to automatically compute breast segmentation in breast MRI. Hence the body breast and air breast surfaces are automatically segmented. By this breast segmentation dice similarity coefficient (DSC) and total overlap values are 0.94 and 0.96 respectively. van der Waal et al. [2] compares different methods for measuring breast density, both visual assessments and automated volumetric density, in a breast cancer screening setting. Van et al. [3] defines about breast body interface by manually in a straight line. The breast value segmentation approach is explained in [4]. Lin et al. [5] presents a fully automatic chest template-based method for cases with different body and breast shapes and different density patterns. Menze et al. [6] introduce a generative probabilistic model that has been designed for tumor lesions to generalize well to stroke images, and the generative discriminative model to be one of the top ranking methods in the BRATS evaluation. Nouranian et al. [7] reduces the segmentation variability and planning time by proposing an efficient learning-based multi-label segmentation algorithm. Alba et al. [8] algorithm for the segmentation of severely abnormal hearts which does not require a priori knowledge of the involved pathology or any specific parameter tuning to be applied to the cardiac image under analysis. Wang et al. [9] used a second derivative information representation by the Hessian matrix to delineate chest wall and air breast boundary.

This paper presents a comparative framework of [1] with brain, chest, heart and liver MRI to automatically segment the above parts of human body. The related work is to compare the technique in [1] with brain, chest, heart and liver segmentation. The above segmentation is verified on 35 MRI cases.

## 2 Material

To evaluate the segmentation process output result, the data set used which consists of atlases of 35 pre-contrast T1-weighted MR breast, brain, chest, heart and liver MRI scans obtained from different patients. For screening test, the ages of the women are between 25 and 68 years. The above MRI examinations were performed on a 1.5T system (Siemens 1.5T), Magnetom Vision). The clinical imaging parameters is [1] used for whole segmentation process (Table 1).

**Table 1** Clinical image parameter

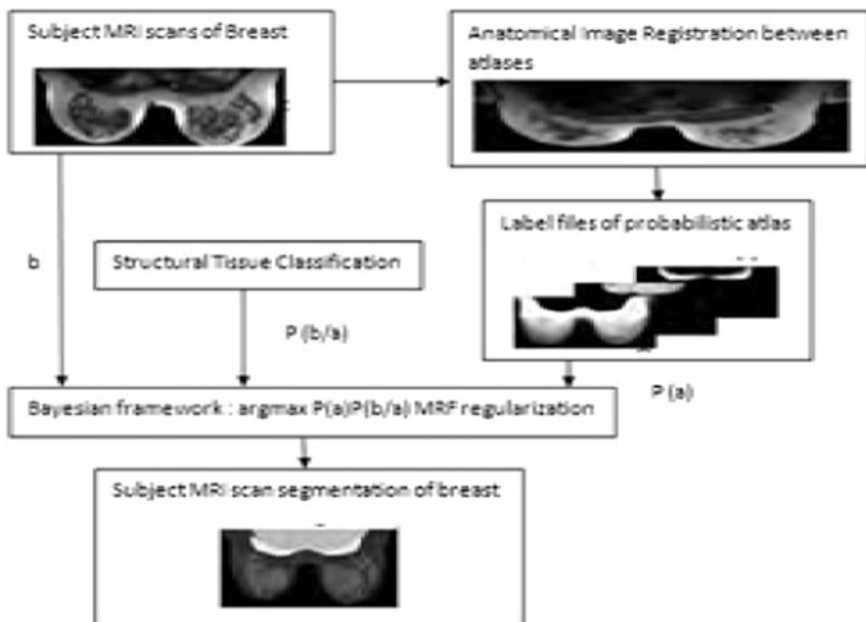
Matrix size	256 × 128 or 256 × 96
Slice wideness	1.33 mm
Slice openness	0.712–1.25 mm
Flip angle	8°, 20°, 25°
Cycle duration	8.1–8.8 ms
Repetition duration	1.8–5.76 ms

### 3 Probabilistic Atlas Based Segmentation in Breast, Heart, Brain, Liver and Chest

The authors of [1] presented a probabilistic atlas based method by using Bayesian framework. This framework is to provide an accurate probability distribution for the above mentioned muscle area. The authors of this article are trying to utilize this method beyond the breast MRI, also in other important body parts like heart, brain, liver and chest. The whole process is completed in SCB medical college, Cuttack, Odisha, under the supervision of one doctor and one MRI technician. Figures 1, 2, 3, 4 and 5 shows the implementation of the segmentation frame work with Bayesian voxel classification logarithm by the use of probabilistic atlas.

### 4 Result and Discussion

In this experiment we evaluate the probabilistic segmentation frame works on 35 patients. Each segmented case was not included for the construction of the probabilistic atlas. The quality of the segmentation was measured by the dice similarity coefficient (DSC) and total over lap (Fig. 6).



**Fig. 1** Probabilistic atlas based segmentation of the pectoral muscle in breast MRI

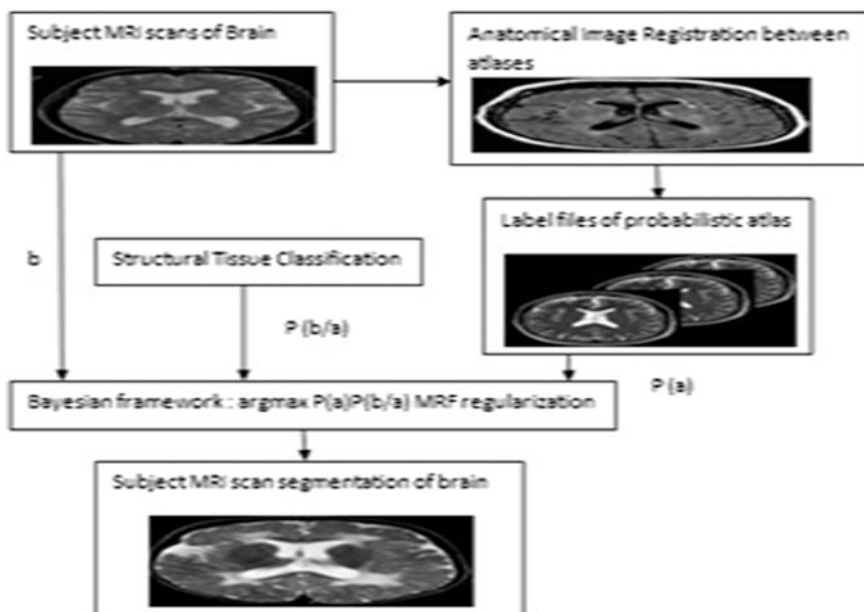


Fig. 2 Probabilistic atlas based segmentation of the pectoral muscle in brain MRI

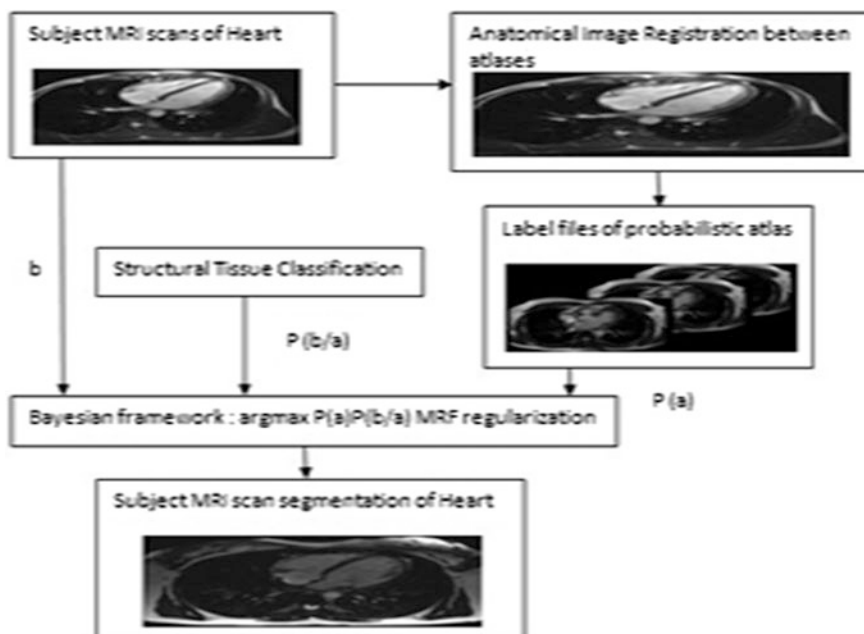


Fig. 3 Probabilistic atlas based segmentation of the pectoral muscle in heart MRI

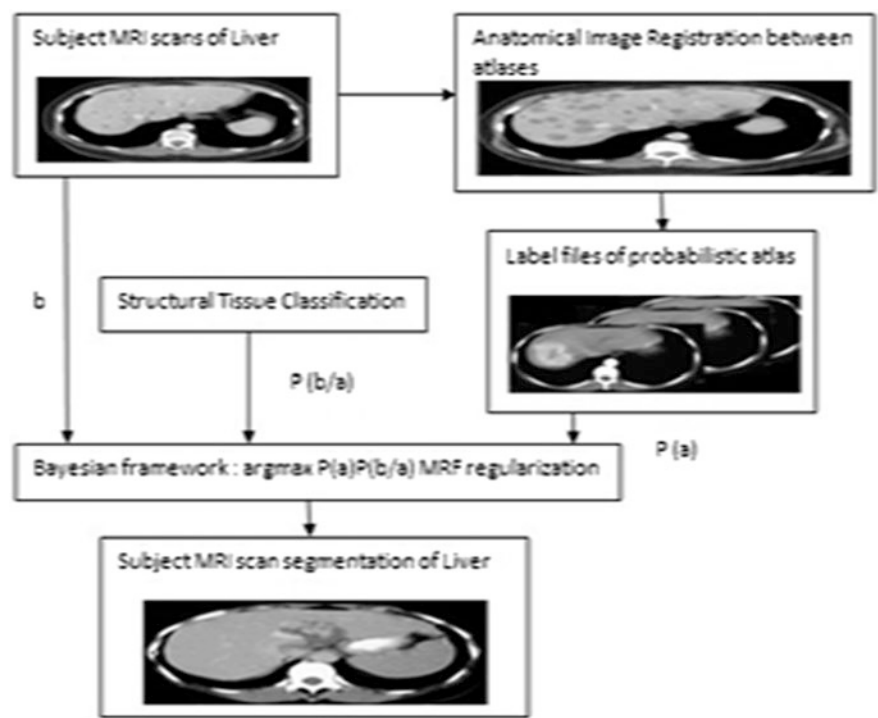


Fig. 4 Probabilistic atlas based segmentation of the pectoral muscle in liver MRI

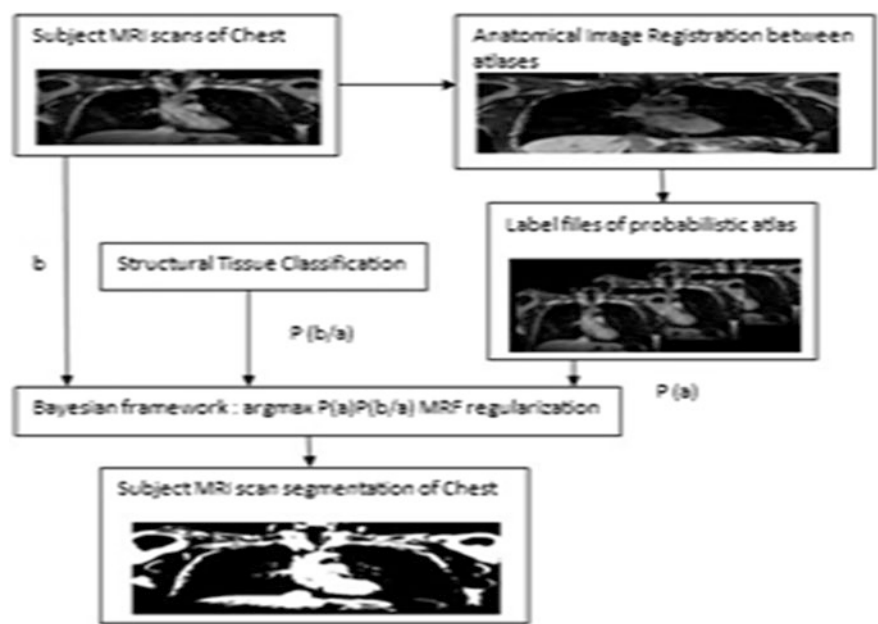
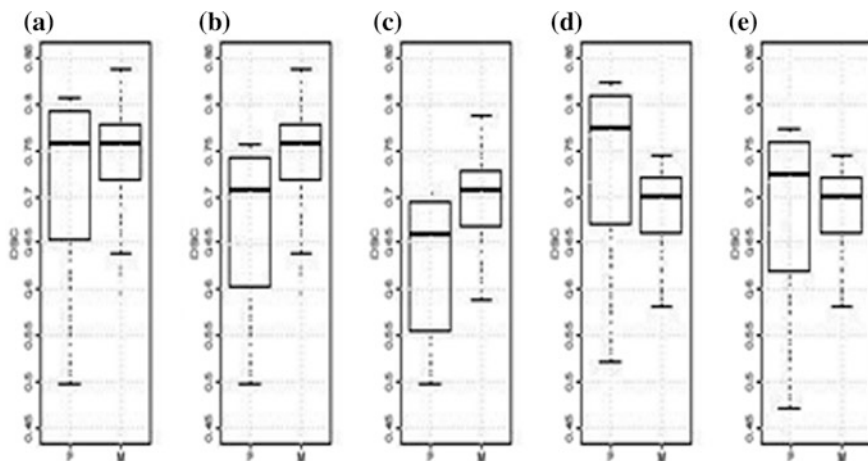


Fig. 5 Probabilistic atlas based segmentation of the pectoral muscle in chest MRI



**Fig. 6** a–e shows box plot of breast, brain, heart, liver and chest showing their DSC report (P) and total overlap (M) respectively using probabilistic segmentation approach

**Table 2** Average DSC and average total overlap obtained from probabilistic atlas segmentation method

MRI of body parts	DSC	Total overlap
Breast MRI	$0.76 \pm 0.12$	$0.76 \pm 0.12$
Brain MRI	$0.71 \pm 0.15$	$0.76 \pm 0.15$
Heart MRI	$0.66 \pm 0.08$	$0.71 \pm 0.08$
Liver MRI	$0.77 \pm 0.12$	$0.70 \pm 0.12$
Chest MRI	$0.72 \pm 0.13$	$0.70 \pm 0.13$

The Table 2 shows the average DSC and average total overlap obtained from probabilistic atlas segmentation methods. The lower DSC value is getting from heart MRI report of  $0.66 \pm 0.08$  as compared to breast MRI  $0.76 \pm 0.12$ , chest MRI  $0.72 \pm 0.13$  and the liver MRI DSC  $0.77 \pm 0.12$ . The report is very much similar to breast MRI DSC report. The total overlap values exceed 0.70 in each MRI case. Finally, since no previous works performed pectoral segmentation in brain, heart, liver and chest MRI. So this is only a comparative study with [1] to show the DSC and total overlap values.

## 5 Conclusion

In this work, the probabilistic atlas based methodology has been studied to perform the pectoral muscle segmentation in a breast, brain, heart, liver and chest MRI. This has not been done previously except breast MRI [1]. Fully dedicated probabilistic frameworks have been utilized and tested on 35 different patients. The obtained results are satisfactory with DSC values.

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