Automatic segmentation of breast lesions in dynamic contrast-enhanced MR images

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Introduction

The interpretation of dynamic contrast-enhanced (DCE) breast MRI data is a complex task for the radiologist and is becoming more so with developments of higher field strength MRI scanners and associated increases in spatial, temporal and contrast information. Several commercial computer-assisted detection/diagnosis (CAD) systems for breast MRI have been developed in recent years to help radiologists with this task. However, these systems at present fall short of automatically locating and classifying malignant lesions. It is not surprising, therefore, that the efficacy of breast MRI CAD remains an open question. A recent review concluded that breast MRI CAD needs to be based on "quantitative features extracted preferably from the automatically segmented 3D lesion" [1]. Herein we present a new approach, temporal score co-occurrence (TSC), to automatic 3D lesion segmentation. It is based on assigning a "suspiciousness" score to each voxel using features extracted from its time series, and then computing the spatial co-occurrence of this score in a 3D neighborhood about the voxel. The results of an empirical evaluation of the efficacy of this technique versus a competing method [2] based on multispectral co-occurrence (MSC) are also presented.

Materials and methods

The DCE-MRI data used in this study originate from routine clinical breast MRI examinations of 32 women performed by Queensland X-Ray, Queensland, Australia over the last two years. The data were acquired on a 1.5T Signa Echospeed (GE Medical Systems) scanner using a 3D FSPGR sequence (typically TR=6.516 ms, TE=3.412 ms, FA=10°). Gadopentate dimeglumine, 0.2 mmol/kg, was administered manually at a rate of about 1 ml/s. Pixel spacing is typically 0.625 mm, slice thickness from 1-1.4 mm, number of post-contrast volumes is from 4-5, and the temporal resolution is around 90 s. The 32 cases were selected because the reporting radiologist identified one or more suspiciously enhancing lesions. In total 45 lesions were identified. The status of all but one was confirmed by cyto- or histopathology: 32 malignant, 16 benign. A 3D segmentation, hereinafter called a VOI, of each was performed by a radiographer using the region-growing tool in OsiriX (http://homepage.mac.com/rossetantoine/osirix). The chest wall and the breast-air boundary were segmented in all of the datasets and excluded from further processing (for computational speed). Three different parametric models of contrast enhancement—linear-slope, Ricker, Hayton—were fitted voxel-wise to each DCE-MRI dataset in turn [3]. The proposed segmentation method (voxel-wise classifier) is depicted in Fig. 1. The data were divided into a training set and a validation set using stratified random sampling (so that each had approximately the same ratio of malignant to benign lesions) in approximately the ratio 2:1. An equal number of voxels (defined to be the number of voxels in the smallest VOI) were randomly sampled from each VOI of the training set to form the class of "suspicious" voxels. This same number of voxels was then sampled randomly from outside each VOI to form the class of "non-suspicious" voxels. For each parametric model, a separate classifier was trained. Training involved the steps of extracting voxel-wise temporal features (including simple features such as time-to-peak and the fitted model parameters), building a *k*-NN classifier to produce a temporal score or probability of "suspiciousness", extracting grey-level co-occurrence features for each labeled voxel in the resulting probability volume, and then training a logistic regression classifier or a support vector machine (SVM) to discriminate between "suspicious" and "non-suspicious" voxels. The co-occurrence features were extracted for each voxel using the $5 \times 5 \times 2$ window shown in Fig. 2 and co-occurrence counts pooled from both slices. The training data was similarly used to train several MSC classifiers. The performance of each resulting classifier, measured in terms of the area under the receiver operating characteristic curve (AUC), was then evaluated on the unseen validation data.

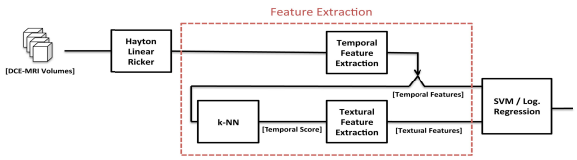

Fig. 1: Proposed (TSC) segmentation method.

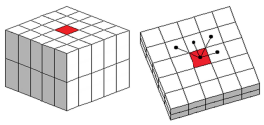

Fig. 2: $5 \times 5 \times 2$ co-occurrence window (left) and in-slice co-occurrence directions (right).

Results and discussion

Table 1 shows the segmentation (classification) results for the 20 classifiers trained: 2 segmentation approaches, three parametric models, two feature selection strategies, two types of classifiers. The results show that the linear-slope parametric model yields the most consistent AUC values across the feature selection and classifier types. In all but one case it also yields the best performing classifiers.

Table 1: Performance of the proposed TSC and reference MSC segmentation methods

Method / parametric model	Sequential forward selection		Stepwise logistic regression	
	SVM	Logistic reg.	SVM	Logistic reg.
TSC / Hayton	0.8621±0.0024	0.8964±0.0022	0.5995±0.0027	0.8957±0.0022
TSC / Linear Slope	0.8345±0.0026	0.8801±0.0023	0.7441±0.0020	0.8989±0.0021
TSC / Ricker	**0.8747±0.0023**	0.8877±0.0022	0.6185±0.0026	0.7000±0.0030
MSC / Hayton	0.8383±0.0026	0.9279±0.0019	0.7298±0.0030	0.9243±0.0019
MSC / Linear Slope	0.8178±0.0027	**0.9330±0.0018**	**0.8671 ±0.0024**	**0.9266±0.0019**

Conclusions

The proposed TSC method achieves a similar level of classification performance to that of the reference MSC method. The advantage of the proposed method, however, is that in contrast to the MSC method, it is not necessary to truncate the range of fitted model parameters in order to construct a co-occurrence matrix. The results demonstrate the efficacy of combining both spatial and temporal variation in tissue enhancement to discriminate between suspicious and normal tissue. They also suggest that it suffices to use the simple linear-slope model, which can be rapidly fitted using least squares, to extract these spatio-temporal features.

References

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