Automated detection of cystic lesions in quantitative T1 liver images

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Abstract. Differentiating between cysts and other liver lesions seen on magnetic resonance images is an important diagnostic problem. Quantitative T1 mapping enables characterisation of liver tissue in vivo, by providing an estimate of the extracellular water content, and can be used in analysis of liquid-filled cysts. This paper presents an image processing method to automatically detect hepatic cysts in such quantitative T1 maps. The method has been tested on a cohort of 926 cases from the UK Biobank study and classified images as containing cysts or cyst-free with accuracy of 83%, sensitivity of 93% and specificity of 82%.

Keywords: hepatic cysts, MRI, liver, image processing.

1 Introduction

With the high prevalence of liver disease and liver cancer worldwide, differentiation between types of liver lesions seen on magnetic resonance images poses a diagnostic problem of increasing significance [1]. Simple hepatic cysts are benign lesions, consisting of a thin wall of cuboidal biliary epithelium filled with serous fluid. They are usually asymptomatic, unless they become of a significant size or number. Most simple hepatic cysts are diagnosed as incidental findings in abdominal radiography and require no treatment. However, polycystic liver disease, which may be caused either by autosomal dominant polycystic liver disease (ADPLD) or associated with polycystic kidneys in autosomal dominant polycystic kidney disease (ADPKD), can cause significant discomfort and requires medical attention. However, therapeutic options are currently limited; liver transplantation is currently the only curative option available [2].

In a recent study by Galvão et al. [3] on the prevalence of cystic hepatic lesions, based on a review of magnetic resonance imaging results of hospital patients, simple hepatic cysts were estimated to occur in 14.5% of the examined population. This result is considerably different to that from a similar study based on a review of ultrasound results by Kaltenbach et al. [4], in which cyst prevalence was found the be 5.8% of the examined population. The authors attribute the differences between the prevalence reported across different studies to the use of imaging techniques with differing sensitivities and differences between the populations studied.

Cystic hepatic lesions may also occur as a result of neoplastic or inflammatory processes (abscess), however such lesions usually have a 'complex' appearance and can be distinguished from simple hepatic cysts through the use of intravenous-contrast enhanced imaging [5]. Definitive identification of simple hepatic cysts on the basis of MR imaging alone could prevent patients from contrast-enhanced follow-up imaging, and reduce the stress associated with the incidental finding of a lesion.

A recent study by Farooq et al. [6] on MRI segmentation methods of polycystic liver concluded that image intensity thresholding produced acceptable results in case of numerous large cysts, however the method performed poorly against less severe disease. Göçeri et al. [7] proposed a method of liver segmentation based on MR data, which included cyst detection, yet the cyst detection method has not been validated against a larger cohort.

Liver*MultiScan*™ is an MR technique that enables characterisation of liver tissue in vivo. First, T1 relaxation maps are acquired using the shortened Modified Look Locker Inversion (shMOLLI) Recovery pulse sequence. This measurement provides an estimate of the extracellular water content, and is subsequently corrected for liver iron content, based on T2* mapping, providing the corrected T1 (cT1) map. The method has so far been successfully used for characterising liver inflammation and fibrosis [8]. However, because of their large content of water, cystic liver lesions are intrinsically distinguishable on quantitative cT1 maps.

In this pilot study, we present a novel method of automatic cyst detection based on a database of quantitative cT1 map images collected from the UK Biobank. Our eventual aim is more precise characterisation and differentiation of incidentally found cystic liver lesions as well as cysts occurring in polycystic liver disease.

2 Materials

The UK BioBank [9] is an extensive resource for evaluating risk factors for later life chronic disease. It contains information regarding lifestyle, clinical, biomarker, and genomic data from a cohort of 500,000 nominally healthy volunteers, who were between 40–69 years of age at the outset of BioBank. Of these, 100,000 are scheduled to have their livers imaged using Liver*Multiscan*.

A training set of 138 BioBank cases, which have single slice shMOLLI liver scans, was used to develop the automatic detection method. Each image was annotated by an expert as either containing cysts or clear. The training set was balanced to include a large number of cases with cysts (approx. 50%), to capture the variation in their appearance, as well as cases free from cysts. Overall, 72 cases in the training set contained a total number of 146 cysts. The images were acquired at the dedicated UK Biobank imaging Centre at Cheadle (UK) using a Siemens 1.5T MAGNETOM Aera scanner. All data was obtained through UK Biobank Access Application 9914.

In Liver*MultiScan* images, cysts appear as oval regions with sharply-defined edges, and they have distinctively high cT1. The boundaries of cysts have a noticeably shorter cT1, comparable to that of blood vessels, which is caused primarily by the partial-volume effect. An example of a cT1 image with cysts is shown in Fig. 1.

Individual cysts were identified and segmented using a semi-automatic method based on intensity thresholding. The cT1 of cysts in the analysed cohort averaged around 2700 ms, compared with normal liver parenchyma (500-800ms). An entirely separate set of 926 randomly selected BioBank cases was used for testing of the developed algorithm. We postulate that because the cT1 of cysts is significantly higher than that of liver parenchyma, image intensity thresholding can be used as a basis for cyst detection. Because of the magnitude of the difference, the result of intensity thresholding provides us with a near-perfect cyst segmentation. However, identifying cysts automatically poses a challenge, because the presence of regions which have similar cT1 values may cause false positive detection.

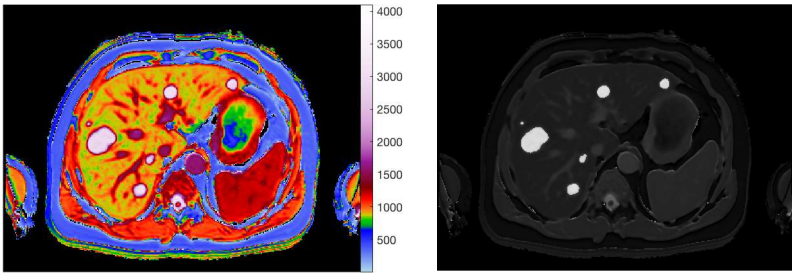

Fig.1. An example of a Liver*MultiScan*^{TM} cT1 image of a healthy volunteer from UKBB containing cysts (the image colourmap represents cT1 values in ms), b) the result of semi-automatic cyst segmentation by an expert.

3 Method

As a first step, a deep convolutional neural network is applied to identify and segment the region corresponding to the liver, as described in detail in a previous work by Irving et al. [10]. The algorithm is trained specifically for segmentation of liver parenchyma and it aims to exclude vessels from the segmentation mask. Then, morphological closing, using a disk-shaped structuring element of radius r = 30 px, is performed to create a filled-in mask of the liver, that also includes vessels and cysts. This is shown in Fig. 2.

Intensity thresholding is performed to find candidate cysts within the liver region. A threshold of cT1 = 2000 ms provided precise outlines of every cyst encountered in the training set. As well as cysts, some additional small regions may be found within the liver. Such regions may occur within blood vessels or bile ducts. They can also result from imaging artefacts or poor cT1 model fitting on the outer borders of the liver.

Because cysts are oval in shape, a 'circularity' measure can be applied to distinguish them from other objects. This is attained through calculation of the eccentricity of every object found. The value of eccentricity is a scalar ranging from 0 (perfect circle) to 1 (a line segment).

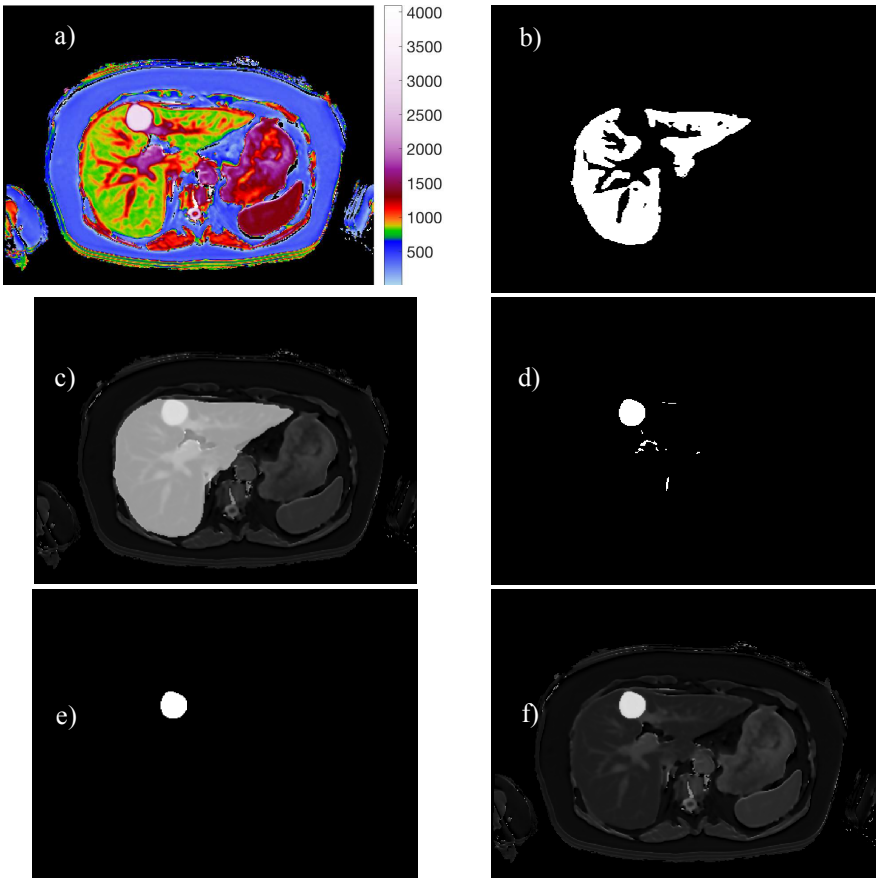

Fig. 2 The proposed image processing pipeline, a) input image, b) the result of liver segmentation, c) 'filled-in' liver mask (shown as a transparent overlay), d) the result of cT1 image thresholding within the liver region, e) 'non-elliptic' objects removed, f) the final result overlaid with the original image.

To be considered a cyst, the object's eccentricity must be below a specific threshold. The value of the eccentricity threshold was established through comparison of the performance of the automatic image classification against classification by expert. The corresponding receiver-operating characteristic curve (AUROC = 0.98) plotted for the training set is presented in Fig. 3. The point corresponding to eccentricity = 0.79 was selected as optimal.

Finally, additional processing steps are applied for removal of small imaging artefacts occurring in some cases at liver outline and each image is classified as either containing cysts or 'clear'.

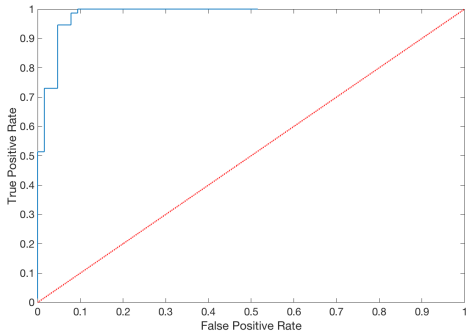

Fig. 3 Receiver operating characteristic curve illustrating the dependence of the results of image classification on the variable object eccentricity threshold, in the training dataset. Point corresponding to FPR = 0.09, TPR = 1 was selected as optimal.

4 Results

The method was validated on a randomly selected set of 926 cases from UK Biobank, featuring healthy volunteers, that should be representative of the general population. Cysts were identified by an expert in 21 persons, which corresponds to a prevalence of 8% over the nominally-normal population.

The proposed cyst detection algorithm showed a total accuracy of 83%, sensitivity of 93% and specificity of 82% comparing to expert annotations (false positive rate of 18%). The high incidence of false positives was found to be caused by a large number of cases where regions with very long cT1 occurred within blood vessels. To reduce the number of false positives, an improved version of the method is proposed. After the current cyst detection pipeline, an additional step can be added which identifies vessels based on intensity thresholding. Cyst candidates found within the much larger vessels regions can be excluded on the basis of the ratio of areas between the "cyst" and the vessel. The expanded version of the method, excluding small cyst candidates occurring in vessel regions showed an accuracy of 93%, sensitivity of 91% and specificity of 93% over the original validation set. An additional, independent set will be used for the validation of the improved pipeline in future work.

5 Discussion

The developed automatic cyst detection method has been found to successfully identify cysts in quantitative cT1 maps. The proposed pipeline is useful for identifying cases of interest in very large cohorts, such as UK Biobank, which in turn can help speed up the analysis. In the future, we will investigate methods based on machine learning for the purpose of creating a more robust method.

The established cyst prevalence of 8% was based on the analysis of single-slice scans only and therefore, is likely underestimated. Because of this, the number cannot be directly compared to those reported in the literature. There is a noticeable trend in the literature on prevalence of simple hepatic cysts, that CT and MR-based studies report a much higher incidence of cysts than those based on analysis of ultrasound or autopsies. Basing on the analysis of cT1 images of UK Biobank volunteers, it is evident that hepatic cysts are exceptionally clearly distinguishable using Liver*MultiScan*^{TM}, and the imaging method can be used with high confidence in future prevalence studies.

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