Reducing over- and Undersegmentations of the Liver in Computed Tomographies Using Anatomical Knowledge

C. Oyarzun Laura\textsuperscript{1,2}, S. Oelmann\textsuperscript{1}, K. Drechsler\textsuperscript{1,2}, and S. Wesarg\textsuperscript{1,2}

\textsuperscript{1} Visual Healthcare Technologies, Fraunhofer IGD, Darmstadt, Germany
\textsuperscript{2} Graphisch-Interaktive Systeme, Technische Universität Darmstadt, Darmstadt, Germany

Abstract—In the last decades several liver segmentation methods have been proposed. The proposed methods go from region growing to the more complex statistical shape models. Despite the robustness of those algorithms, liver segmentation is still a challenging task especially in areas in which its neighboring organs have similar intensities, e.g., heart and ribcage. In addition to this, pathological organs that contain tumors near their surface present additional difficulties. This paper presents a solution to increase the accuracy of those algorithms in the aforementioned areas. The effect of the improvement using the generated heart and ribcage walls (7\% and 1\% respectively) is evaluated on 9 clinical computer tomographies (CT). The improvement (12\%) when tumors are near the surface, on the contrary, is tested on 7 clinical CT images.

Keywords—Liver, segmentation, oversegmentation.

I. INTRODUCTION

The importance of liver segmentation for clinical applications has been proved in the past. Segmentation methods are used for planning and diagnosis. Furthermore, the results of segmentation methods are also an important starting point for several navigation and outcome validation tools. Consequently, segmentation has become one of the main focuses of research for medical image processing. Despite the amount of proposed methods, liver segmentation is still a challenging task, especially in areas where the neighboring organs, e.g., heart or ribcage, have similar intensities as the liver. Groups working on this field have presented solutions to solve those difficulties. Peng et al.\textsuperscript{[1]} detect boundaries between neighboring organs in areas with low gradient information using a series of context descriptors: the distributions of the image intensity, the local binary pattern and the local variance. Gauriau et al.\textsuperscript{[2]} generate the bounding boxes of liver and heart using regression forests. Then the heart is roughly segmented by means of a shape model to fit the bounding box. The segmented heart is used to prevent leakages of the liver into the heart. Narkbuakaew et al.\textsuperscript{[3]} opt for thresholding and morphological operations to generate a mask containing all the information enclosed by the ribcage and vertebrae. Maier et al.\textsuperscript{[4]} generate a series of seed points at the ribs that will be considered background by their random walk algorithm. These points are detected based on the high bone intensities. When no ribs are detected approximate points are added. Chi et al.\textsuperscript{[5]} constrain their snake using k-means clustering to prevent leakages into the heart. The leakage into the ribcage is prevented with a combination between thresholding and edge enhancement techniques. Ruskó et al.\textsuperscript{[6]} propose to generate a surface that constitutes the boundary between heart and liver using the lungs as reference. They detect a series of points between both lungs using largest gradients, and assume that they are in the boundary between liver and heart.

The idea of using the lungs as reference for the boundary detection is promising. Unfortunately, the gradients between heart and liver are not always clearly visible. Furthermore, in some areas the largest gradients do not belong to the searched boundary. Following the aforementioned idea, in this paper we propose a method that automatically filters out edges that do not belong to the boundary. The method is enhanced with a robust outlier detector. Furthermore, we present a fully automatic ribcage estimation. Opposite to the aforementioned methods, we detect points not only at the ribs but also at intermediate points, which allows us to generate a more accurate estimation of the ribcage surface. The cited works keep returning inaccurate results when the liver contains tumors near the surface. Here we propose to reconstruct the liver by replacing the tumor with an intensity profile of healthy liver tissue.

II. METHODS

In this section the methods proposed to prevent leakages in the boundary between liver and heart (Section A.) and in the boundary between liver and ribcage (Section B.) are proposed. Both methods follow the work flow shown in Fig. 1. First, a series of reference points are detected at the lung contours. Then, an edge image is generated and used to create an initial set of points at the searched boundary. An outlier detector serves to refine the initial set of points. Finally, a
smooth surface and consequently a mask are used to avoid segmentation errors in those areas. Besides, a method is presented to avoid erroneous undersegmentation of the liver due to the presence of tumors near the surface (Section C.).

A. Heart

As it was mentioned before, one of the areas prone to leakages during the liver segmentation process is the boundary between liver and heart. A thorough examination of clinical CT datasets shows that this boundary is located in the neighborhood of the plane connecting the lower leftmost part of the right lung (Fig. 2 (a) green) and the lower rightmost part of the left lung (Fig. 2 (a) yellow). The green and yellow points shown in the figure will be considered the reference points in this section. The first step of the process, namely, the detection of those reference points is done similarly to Ruskó et al. [6]. Fig. 3 serves to explain this process. The lungs are initially segmented using a combination of thresholding and morphological operations. Fig. 3 shows the lung contour (orange) of a coronal slice. In each coronal slice $c_i$ a point $W_i$ is selected with the lowest and rightmost (or leftmost for the left lung) coordinates seen in the lung in $c_i$. Then, the yellow/green reference point is detected as the closest lung point to $W_i$ (Fig. 3). After all reference points are detected each coronal slice will contain two points, one for each lung. These two points are then connected to form the initial estimation of the boundary between heart and liver. This is illustrated as an orange line in Fig. 2 (a).

Nevertheless, this initial boundary is only an estimation that has to be refined. Therefore, it is desirable to move this boundary towards the edges that can be seen in its neighborhood. However, not all the visible edges belong to the searched boundary and should therefore be removed. The edges in the boundary between heart and liver are nearly horizontal. A directional edge detection is carried out to filter out all edges that do not fulfill that condition. To this end a recursive Gaussian filter is used [7].

A series of denoising and morphological operations follow to remove spurious edges. The used parameters have been determined empirically. First a Gaussian operator is used to smooth the edge image resulting from the previous step [8]. The resulting image is thresholded and only those edges with intensity values between 3 HU and 300 HU are kept. The thresholded binary image is eroded using a structuring element with a radius of 1. This last step eliminates artifacts caused by noise. The edges of interest belong to locations of the CT image with low intensities. Thus, the eroded image is further filtered to eliminate those edges that do not fulfill that condition. Consequently all edges with an intensity in the CT image lower than -50 HU are removed from the edge image. The remaining edges are visible in red in Fig. 2 (a). These edges will be used for the refinement of the initial estimate of the boundary.

Therefore, the points that form the initial boundary are moved in search of edges near the initial contour (red edges and violet arrows in Fig. 2 (a)). The result of this is a set of $k$ new points, $P = \{P_j : j \in \{0,k\}\}$, located at the edges. Nevertheless, some detected points are outliers, caused by remaining spurious edges (e.g., blue circle). Thus, an outlier detector is needed to ensure the accuracy of the results. Let