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FCN Based Approach for the Automatic Segmentation of Bone Surfaces in Ultrasound Images

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Abstract

In CAOS, ultrasound imaging has been proposed as a solution for obtaining the specific bone morphology of the patient, avoiding limitations of existing technologies. However, this imaging modality presents different drawbacks that make difficult the automatic bone segmentation. A new algorithm, based on Fully Convolutional Networks (FCN), is proposed. The aim of this paper is to compare and validate this method with (1) a manual segmentation that was performed by three independent experts, and (2) a state of the art method called Confidence in Phase Symmetry (CPS). The FCN based approach outperforms the CPS algorithm and the RMSE is close to the manual segmentation variability.

1 Introduction

In orthopedic surgery, the intraoperative determination of the patient specific bone morphology is crucial to accurately perform a surgery. Fluoroscopy is often used for this purpose. However, this modality exposes the patient to additional x-rays. In addition, this kind of images are only 2D projections of the internal bony structures which can lead to misinterpretations.

During the last decades, some studies tried to integrate the radiation-free, real-time ultrasound (US) modality in order to acquire the bone morphology without additional incisions or x-ray radiographs [1].

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The three dimensional (3D) position and orientation of the US image is determined thanks to (1) a marker localized by the CAOS system and attached to the US probe, and (2) an accurate image to probe calibration [2]. The main difficulty to make this technology usable in the operating room is to achieve an automatic bone segmentation of the US images. The high level of noise, imaging artefacts [3], limited field of view, reverberations and shadowing [1] could affect the quality of the images.

Deep-Learning based methods should be investigated for the segmentation of bone in US images since these approaches have achieved very successful results in biomedical image segmentation [1, 4–6]. A few studies have recently used Deep-Learning algorithms for the bone segmentation in US images. [7, 8] . These recent Deep-Learning based methods seem to outperform others previous approaches.

All these algorithms were however assessed and compared to a manual segmentation performed by only one expert. Since the interpretation of the bone interface in US images could be different following experts, the manual segmentation cannot be considered as an absolute gold standard without having first evaluated it.

In this paper, we propose a new algorithm inspired by the concept of the hybrid CPS method introduced by Quader et al. [9]. As this CPS approach, our algorithm uses a combination of the local Phase Symmetry (PS)[10] and the confidence map [11]. However, the classification of the bone surface is performed using FCN [12].

The aim of this paper is to compare the developed method with (1) a manual segmentation that has been previously evaluated by three independent experts, and (2) the CPS algorithm.

2 Materials and Methods

The proposed approach is based on the FCN algorithm described in [12] which is well suited for segmentation purpose thanks to the classification of each pixel in the image. The input of the algorithm is an image composed by three colors (Red, Green , and Blue) in which each one contains respectively the ultrasound image, the phase Symmetry image and the Confidence Map (figure 1).

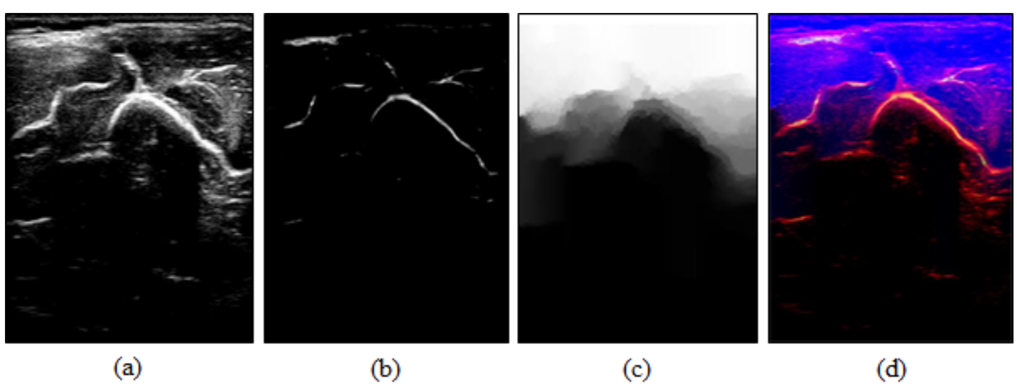

Figure 1: US image in the red channel (a), phase-symmetry in the green channel (b), confidence map in the blue channel (c) and combination of the three RGB channels (d)

The dataset used for this study is composed of 3692 US images collected from three volunteers on six different anatomical structures. Three experts manually delineated the bone interface on these US images. The inter- and intra- observer variabilities of this manual delineation was assessed. Both FCN based and CPS approaches were studied and compared to the inter-observer average segmentation according to six criteria: recall, precision, F1-Score, accuracy, specificity and Root Mean Square Error (RMSE).

3 Results

3.1 Manual segmentation analysis

The intra- and inter-observer variabilities were inferior to 0.8 mm for 90% of manual annotations.. The mean ± Standard Deviation (STD) are 0.33 ± 1.02 mm and 0.21 ± 0.43 mm for respectively the inter- and the intra-observer variabilities. The maximum values are 38.10 mm and 20.59 mm for respectively the inter- and intra-observer variabilities.

3.2 FCN based approach results

For 75% of predictions, the RMSE of the FCN based approach is inferior to 0.48 mm The mean ± Std of the RMSE was 0.99 ± 2.62 mm and 6.43 ± 7.66 mm for respectively the FCN based approach and the CPS algorithm. The mean recall, precision, f1-Score, accuracy and specificity were respectively 66%, 65%, 62%, 81% and 84% for the FCN based approach, and 64%, 36%, 41%, 50% and 41% for the CPS algorithm.

4 Discussion and Conclusion

We performed a first study to evaluate the inter- and intra-observer variabilities of the manual annotation of bone interfaces in the US images. Most of the annotations have an inter and intra-observer variability between an acceptable range. However, maximum values of inter and intra-observer variability, that are widely far from a correct value, are due to misinterpretations during the annotation [1].

Regarding the algorithm study, the FCN based approach shows better classification scores than the CPS method. As also observed by Ozdemir [3], the mean RMSE for the CPS algorithm reaches more than 5 mm. This is much higher than the RMSE of the FCN based approach, which is 0.99 ± 2.62 mm. The accuracy of the algorithm is therefore close to the manual segmentation uncertainty.

In conclusion, we have shown in the paper that (1) the FCN based approach outperforms the CPS method and (2) the accuracy of the FCN based approach is close to the manual segmentation variability.

5 References

1. Hacihaliloglu I (2017) Ultrasound imaging and segmentation of bone surfaces: A review. Technology 5:74–80 . doi: 10.1142/S2339547817300049
2. Mercier L, Langø T, Lindseth F, Collins LD A review of calibration techniques for freehand 3-D ultrasound systems. doi: 10.1016/j.ultrasmedbio.2004.11.001
3. Ozdemir F, Ozkan E, Goksel O (2016) Graphical modeling of ultrasound propagation in tissue for automatic bone segmentation. Lect Notes Comput Sci (including Subser Lect Notes Artif Intell Lect Notes Bioinformatics) 9901 LNCS:256–264 . doi: 10.1007/978-3-319-46723-8_30
4. Ronneberger O, Fischer P, Brox T U-Net: Convolutional Networks for Biomedical Image Segmentation
5. Moeskops P, Wolterink JM, Van Der Velden BHM, Gilhuijs KGA, Leiner T, Viergever MA,

Išgum I Deep Learning for Multi-Task Medical Image Segmentation in Multiple Modalities
6. Litjens G, Kooi T, Bejnordi BE, Setio AAA, Ciompi F, Ghafoorian M, van der Laak JAWM, van Ginneken B, Sánchez CI (2017) A Survey on Deep Learning in Medical Image Analysis. doi: 10.1016/j.media.2017.07.005
7. Salehi M, Prevost R (2017) Precise Ultrasound Bone Registration with Learning-Based Segmentation and Speed of Sound Calibration. 10434:682–690 . doi: 10.1007/978-3-319-66185-8
8. Baka N, Leenstra S, van Walsum T (2017) Ultrasound Aided Vertebral Level Localization for Lumbar Surgery. IEEE Trans Med Imaging 36:2138–2147 . doi: 10.1109/TMI.2017.2738612
9. Quader N, Hodgson A, Abugharbieh R (2014) Confidence weighted local phase features for robust bone surface segmentation in ultrasound. Lect Notes Comput Sci (including Subser Lect Notes Artif Intell Lect Notes Bioinformatics) 8680:76–83 . doi: 10.1007/978-3-319-13909-8_10
10. Kovesi P (1997) Symmetry and asymmetry from local phase. Tenth Aust Jt Converence Artif Intell 190:2–4 . doi: 10.1.1.40.4146
11. Karamalis A, Wein W, Klein T, Navab N (2012) Ultrasound confidence maps using random walks. Med Image Anal 16:1101–1112 . doi: 10.1016/j.media.2012.07.005
12. Long J, Shelhamer E, Darrell T (2015) Fully Convolutional Networks for Semantic Segmentation ppt. Proc IEEE Conf Comput Vis Pattern Recognit 3431–3440 . doi: 10.1109/CVPR.2015.7298965