Contributions of Artificial Intelligence to low resolution Renal Multiparametric Magnetic Resonance Analysis

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***Abstract*—Arterial spin labeling (ASL), is a Multiparametric Magnetic Resonance Imaging (MRI) technique used to quantify and evaluate Renal Blood Flow (RBF) and detect perfusion failure by labelling blood water as it flows throughout the kidney. This study aims at providing an automatic quantifying and evaluation tool for Chronic Kidney Disease (CKD) patients's follow-up.**

I. Introduction

Chronic Kidney Disease (CKD) is a conditon characterized by a gradual loss of kidney function over time [1]. It is estimated that the 10% of the population suffer from CKD and is expected to continue to grow, due to aging and increased incidence of diabetes and obesity. In patients with advanced CKD, renal transplant improves quality of life and increases survival rate. In recent years, the incidence of acute rejection has been considerably reduced and early loss of implant has been minimized. However, the causes of the progressive deterioration of the implant are various and its mechanisms are unknown. For that reason, postoperative renal implant evaluation is a complex diagnostic problem.

In the presented research project, dataset from 18 renal transplanted patients was used, approved by the Ethics Research Committee of the University of Navarra. ASL-MRI scans were performed on a 3T Skyra using an 18-channel body-array coil. Perfusion images were acquired using a *pseudo continuous arterial spin labeling (PCASL)* sequence [2].

II. Motion-Correction Techniques

Motion correction methods are a prerequisite in multiple-image registration tasks. We implemented a non-rigid group-wise registration with PCA2 metric [3]. The method aligns volumes on a slice-wise basis. We compared the registration method without focusing on a *Region of Interest (ROI)* and within a ROI. The ROI in each slice of the volume was manually marked and subsequently dilated to encompass whole renal area. The registration was implemented in Elastix [4].

After image registration, *Perfusion Weighted Images (PWI)* maps were extracted by subtracting registered control and label images.

Temporal Signal to Noise Ratio (tSNR) was computed as the ratio of the mean to the temporal standard deviation, as a measure of signal stability. Outliers were discarded when the ASL signal was more than 2 standard deviations (SD) away from the global mean [2]. Manually defined and sub-sequently eroded ROI on the cortex was used to measure the tSNR along ASL pairs. Motion correction techniques show statistically significant improvement ($p<0.025$) on the tSNR. No statistical difference was found between two registration approaches in terms of temporal signal variation of the images ($p>0.025$). However, our dataset presents high inter-subject variability, to which groupwise registration method is highly dependent on. For that reason, for those tSNR samples higher than mean tSNR, RR method shows statistically significant difference ($p<0.025$) on tSNR mean, compared to NRR method, indicative of a more successful image alignment.

III. Kidney Segmentation

Kidney parenchyma's segmentation serves as quantitative analysis [5] tool for renal damage prevention, which requires time-consuming pixel-wise annotation. Nonetheless, *Machine Learning (ML)* based medical image segmentation has shown its value in segmentation of several organs. *Supervised Descent Method (SDM)* is a cascaded regression approach that learns generic descent directions in a supervised way [6]. Besides, the *U-NET* is a widely used non-supervised *Convolutional Neural Network* for medical image segmentation. It consists of a contracting path to capture context and a symmetric expanding path that enables precise object localization [7]. We proposed the *Cascaded Weighted UNET-SDM (CUS)* model, consisted on the automation of SDM for kidney segmentation, based on preliminary trained UNET's result initialization.

First, the UNET was trained on augmented data and introduced sample weights in the Dice loss function. It was minimized via *Adam* optimizer and learning rate of 1x10-

4, with a batch size of 16 and 100 epochs. Training and testing of the model was implemented on Python 3.8 using Tensorflow as backend on GPU NVIDIA GeForce RTX 3090. Secondly, we used *Histogram of Gradient (HOG)* extraction to encode local shape information from point locations within the image. We used 40 landmarks and 100 initializations. Initial shapes for training were translated ground truth masks with additional independent noise applied to each landmark and testing was performed on kidneys' mean shapes. The algorithm was implemented in Matlab on Intel(R) Core(TM) i5-7500 CPU.

The prediction accuracy of CUS was evaluated in terms of *Dice Score (DS)* similarity index. Proposed architecture achieved statistically higher score mean compared to original UNET ($p<0.005$). Besides, it showed an outstanding segmentation accuracy ($DS = 0.850 \pm 0.028$) and statistically higher performance, comparing with the original UNET. These accurate image segmentation models enable functional and structural information extraction, including kidney detection and shape estimation.

Discussion

Our results demonstrated the applicability of both groupwise registration and parenchyma's segmentation process on postoperative renal implant evaluation. We achieved to counteract the misregistration of control and label images to subsequently extract whole kidney mask for each image. Furthermore, the kidney detection process serves as a reference for further RBF calculation methods.

IV. Challenges and Future Work

The implementation done in these initial steps has provide a good starting point for further research.

Coarse-to-Fine Segmentation

Innovative Coarse-to-Fine approach could be performed to improve ML based segmentation results. Mask R-CNN is a pixel-based Instance Segmentation model that adds an extra parallel branch on Faster-RCNN to segment instances within predicted boxes [8]. Renal ASL-MRI are low resolution images and present other highlighted organs as the bladder, which worsens the final segmentation result. The implementation of these kind of models could improve kidney's edge detection, from firstly detected kidney's bounding box. The training process should be adapted to volumetric grayscale data.

Segmentation of Renal Compartments

The segmentation of renal cortex and medulla has its value on functional kidney evaluation. Despite the development of tools for the segmentation of entire kidney, there is a lack of renal compartments segmentation tool development. Besides, the majority of techniques are implemented on CT or DCE-MRI (high-contrasted images).

In this project, in order to implement a multi-class segmentation tool for kidney cortex and medulla detection and segmentation, we used T1-maps. T1-mapping images were generated from registered T1-images using non-registered groupwise method and PCA2 metric. It is also necessary

to segment the kidney as a whole. Among renal multiclass segmentation techniques intensity-based thresholding is the most simple one. It requires manually defined threshold for each T1-map. Fig. 1 depicts medulla segmentation example based on manually defined and histogram based threshold definition. Despite its simplicity and low computation time, human interaction and parameter setting is needed.

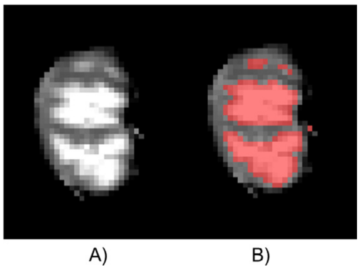

Figure 1. Example result of intensity-based thresholding of renal medulla. A) T1-Mapping image. B) Segmented medulla.

We initially discarded CNN model implementation, as it requires both cortex and medulla regions annotation. However there are different and more complex approaches that provide robust segmentation results:

- *Region Growing* methods and *Shape based* approaches with active contours.
- *Gaussian Mixture Models (GMM)* implementation, where kidney image segmentation is performed by fitting a mixture model that is a composition form of several Gaussian distributions to intensity histograms [9].

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