Using Supervised Graph Embedding for Measuring Glomerular Number from Kidney MRI Images

Jayaraman J. Thiagarajan, Karthikeyan Natesan Ramamurthy, Berkay Kanberoglu, David Frakes and Andreas Spanias

***Abstract*—**

I. Introduction

A. Glomerular Number Estimation

In mammalian kidneys, *nephrons* filter blood to form urine, and a network of capillaries called the *glomerulus* found in the beginning of each nephron, performs the first step of this filtering. The variations in the number and size of glomeruli have been linked to several renal and systemic diseases [**?**], [**?**]. Though approaches such as acid maceration [**?**] and the dissector/fractionator stereology technique [**?**] currently exist for measure the glomerular number and size, they require the destruction of the entire kidney. On the other hand, conventional histological methods determine the overall glomeruli statistics by extrapolating the measurements obtained from a few isolated sections. Consequently, these methods do not perform direct measurements and cannot localize the identified glomeruli to specific parts of the kidney. To address these challenges, the authors in [**?**] proposed a robust, non-destructive technique based on magnetic resonance imaging (MRI) to measure the number and size of glomeruli. This method accurately identifies the glomeruli by injecting cationic ferritin (CF), which causes a decrease in the MRI signal at the location of the glomeruli. The authors demonstrated that the glomerular counts obtained from the 3D MRI images were consistent with the standard histological procedures, while making the measurements in the entire kidney. A sample axial kidney image from 3-dimensional (3D) magnetic resonance imaging (MRI) data obtained for a CF-injected rat is shown in Figure **??**.

In this paper, we are interested in the estimation of the glomerular count from kidney MRI images. The problem of counting number of instances of an object in images (and videos) has been considered in the computer vision literature, and a number of approaches have been developed []. Several existing approaches are limited by their non-robustness to overlapping objects and noise, inability to provide accurate results when the objects are non-uniform, and need for time-consuming inference. Furthermore, approaches that avoid the hard problem of object detection, and take into account the spatial relationships between different local regions have been shown to provide superior results [].

II. Background

A. Kidney MRI Background

B. Counting Objects in Images

Unsupervised methods typically cluster (or group) local regions based on some notion of similarity and obtain the counts []. However, the performance of fully unsupervised methods is often limited, and this has driven the use of supervised approaches. The existing set of supervised techniques can be broadly classified into three categories: (i) detection-based; (ii) regression-based; (iii) segmentation-based. The first approach attempts to build an object detector that localizes the multiple instances of an object, and counts the number of detections. However, building a robust object detector is extremely challenging []. In particular, overlapping objects and noise can severely afftect its performance of may existing object detectors. For example, the strategy adopted in [] performs (local) non-maximum suppression of the confidence map, generated using an object detector, and locates the object instances. The second class of techniques avoid the difficult problem of detecting objects, by inferring a mapping (regression function) from features, that describe the global image characteristics, to the total number of objects []. Though a wide-variety of sophisticated tools exist to learn the regressor [], this approach relies heavily on the choice of the features, and it ignores information regarding the location of the objects.

C. Graph Embedding

D. Building Affinities for Union of Subspaces

III. Overview of the Proposed Approach

IV. Algorithm Description

A. Pre-processing

B. Segmentation using Supervised Graph Embedding

C. Obtaining Glomerular Count

V. Experiments

A. Dataset

B. Benchmark Methods

C. Results

D. Discussion

VI. Conclusions