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LUNG ALLOCATION PIPELINE: MACHINE LEARNING APPROACH TO OPTIMIZED LUNG TRANSPLANT

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ABSTRACT

Lung donation is the most risky transplant procedures. With low survival rates, and poor acceptance of donated lungs, those in need of a lung transplant are at high risk of dying. One reason for poor outcomes is the lack of optimal match between donor and recipient when it comes to lung size and shape. Lungs that do not properly fit in the recipient's chest cavity can fail to inflate fully and quickly start to deteriorate. In such patients, lung contusions can form, edema occurs in healthy lung tissue, and overall lung function declines. To improve patient outcomes after lung transplant, we describe here a developed a computational pipeline which enables donor lungs to be properly matched to recipients. This tool uses CT scans from both the donor and potential recipients to calculate how anatomically different the sets of lungs are, and therefore provide improved matches in both size and shape for the donor lungs.

Keywords: lung transplant, 3D segmentation, machine learning

1 Introduction

Currently in the United States, about 2,500 lung transplants are performed every year. These lung transplants are hopefully life-saving procedures for many people. However, the survival rate for lung transplant recipients is the lowest among all types of organ transplants; with a little over 50% of transplant recipients surviving after five years [1]. Lung donation acceptance rates are also lowest among all organs types, with only 15% of donated lungs accepted for transplant [2].

One challenge facing transplant surgeons is often the size matching of lungs. The lung allocation process takes into account the recipients' lung allocation score, the blood type match, and the distance between recipients, their hospital, and where the donor is located. The lung allocation score is calculated using several functional evaluations for lung health, but does not include anatomical parameters [3].

Today, lung donors and recipients are not matched based on lung size or shape. Many factors create a barrier to including lung size as a criterion. One reason it can be difficult to assess lung size is the lack of available measurement tool. For example, tidal volume cannot be readily assessed accurately in an unconscious patient.

Transplanted lungs which are not well size-matched lead to serious post-procedure complications in the recipient. Specifically, primary graft dysfunction (PGD) is a severe injury that can occur within the first 72 hours of a transplant and has been identified as the leading cause of early mortality after transplant. Around 30% of lung recipients develop PGD [4]. In these patients, PGD is commonly diagnosed using imaging; most commonly chest x-rays and computed tomography (CT) scans. Opacity in one of these scans indicates how diseased the lung graft is. Development of PGD can be partially caused by trauma to the lung during transplant. Contusions can lead to fluid build-up within the alveoli which causes opacity on scans. Trauma due to over- or under-sized lungs placed within the chest cavity is a direct result of mismatched lung transplants.

However, today, pre-operative CT scans are commonly taken of both the donor and recipient during the preparatory process for transplantation. From these scans, lung volumes can be segmented and utilized to generate 3-dimensional object files to analyze. Through machine learning, lung size and shape comparisons can be made computationally so to determine the best size match for lung transplantation. Figure 1 shows the processes involved during lung transplant procedures. The software tool presented in this work would be utilized during the lung allocation process.

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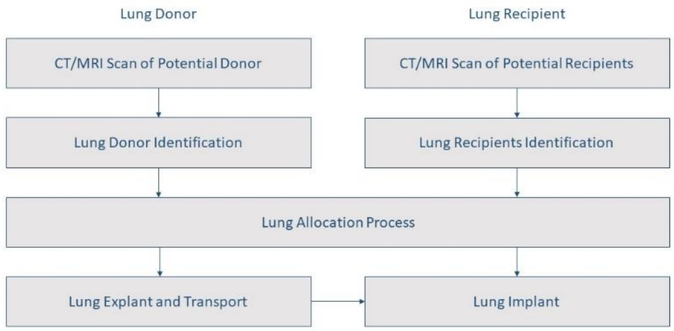

Figure 1: The processes involved to complete a lung transplant and how they relate to the each other. The proposed tool would be used during the Lung Allocation Process.

2 Methods

Eleven human cadaver CT scans were obtained and segmentations and 3D computational object models of the lungs were generated from each. From the eleven lung models, one was randomly selected to represent a lung donor. The donor lungs were compared to the other 10 lung models so to mimic each potential recipient. The lung objects were converted to a 3D point cloud and then compared using a k-nearest neighbors (K-NN) approach. Through K-NN analysis, lungs were compared based on both shape and size. The differences between the donor lung and each potential recipient lung were compared.

2.1 Lung Segmentation

CT images from human cadavers were imported to Materialise Mimics® software to manually segment the lungs from each scan. Figure 2 illustrates this process of manual segmentation.

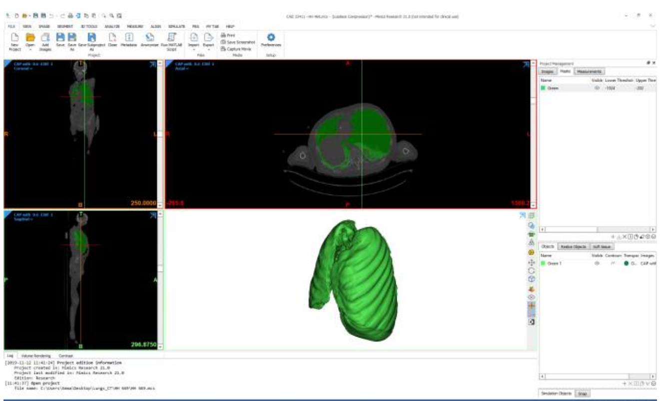

Figure 2: Materialise Mimics® software with segmented lungs.

The objects created in Materialise Mimcs® are exported to a stereolithography (STL) file for analysis. Figure 3 shows examples of the different lung objects. It is clear that this dataset contains a variety of lung shapes and sizes.

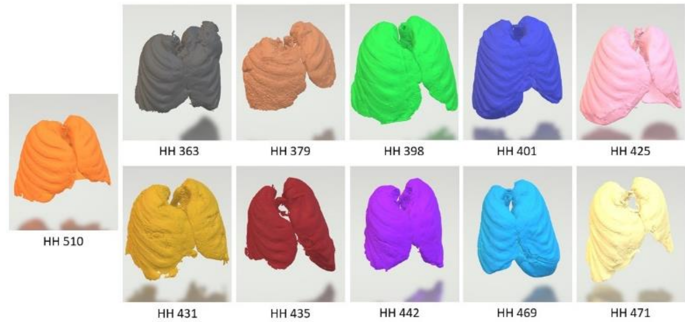

Figure 3: Eleven 3D objects modeled from cadaver lungs.

2.2 Point Cloud Conversion and Analysis

K-NN was used to make a comparison between the donor lungs and each of the potential lung recipients. The 3D lung objects were converted into 3D point clouds to allow for easier implementation of this K-NN analysis. For each point in the 3D point cloud of the donor lungs, the five nearest points in the 3D point cloud of the recipient lungs were calculated via Euclidean distance and indexed. The mean of the five nearest neighbor points was calculated to determine a representative single nearest point on the recipient lung for each point on the donor lungs. Next, the Euclidean distances (measured in mm) between the original points on the donor lungs and the representative points on the recipient lungs were calculated. This process was then repeated for every point on the donor lungs. The average distances between each point on the donor lungs and its representative point on the recipient lungs were then calculated. These average distance measurements approximate the average transformations that map points on the donor lungs to corresponding points on the recipient lungs. As such, it serves as a similarity metric since small values indicate that the lungs are of similar size and shape.

3 Results

This methodology was applied between the designated donor lungs, HH510, and all 10 potential recipient lungs. The average distances required to map points on the donor lungs to the recipient lungs were calculated and recorded in Table 1. These results can be compared to the 3D lung objects for each patient in Figure 2, where lungs that appear similar in shape and size to the donor lungs have a small average distance reported in the table.

Potential Recipient Lungs	Average Distance (mm)
HH363	12.84
HH379	26.64
HH398	9.66
HH401	9.54
HH425	8.82
HH431	10.47
HH435	13.13
HH442	17.32
HH469	15.95
HH471	12.38

Table 1: Each of the potential recipient lungs and the average distances required to map points from the donor lungs onto a corresponding points on the recipient lungs.

Since patient HH425 had the lowest average distance reported, these results indicate that they are the closest match to our donor lungs and would be the best recipient to receive these lungs as a transplant. A 3D scatterplot depicting the point cloud of both the donor lung and prospective recipient lungs are depicted in Figure 4.

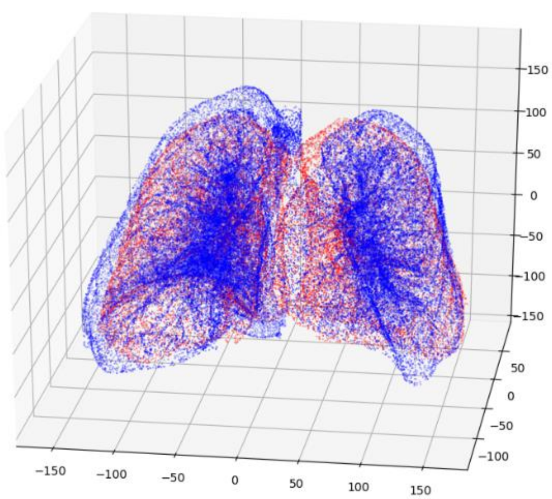

Figure 4: A 3D scatterplot depicting the donor lungs (HH510) in red and the best fit recipient lungs (HH425) in blue.

In addition, a 3D quiver plot displays a vector that represents the distance required to map points from their location on the donor lungs to their representative points on the recipient lungs. In such maps one may easily see differences even between the right and left lungs per patient. Additional metrics could also be developed to express this difference through virtual lung transplantations.

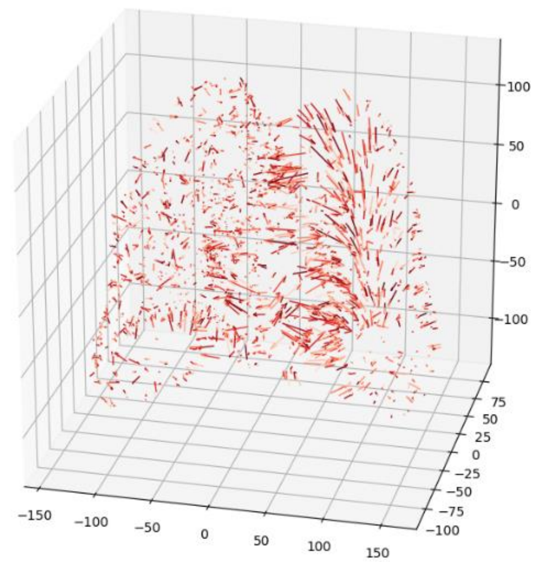

Figure 5: A 3D quiver plot displaying the distances required to map points from the donor lungs (HH510) onto the best recipient lungs (HH425).

4 Conclusion

Finding a best match utilizing virtual lung transplantations, prior to lung donations, could lead to decreases in PGD and increase the survival rates after transplant. The pipeline developed in this work, requires no additional physical strains on the donor or recipient. Additionally, using a computational approach, minimal time needs to be added to the allocation process. With a simple means to analyze lung sizes and shapes, this approach will help physicians and transplant surgeons provide better care for those in dire need of these life-saving procedures.

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