Deep Learning for Personalized Preoperative Planning of Microsurgical Free Tissue Transfers

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Abstract

Breast reconstruction surgery requires extensive planning, usually with a CT scan that helps surgeons identify which vessels are suitable for harvest. Currently, there is no quantitative method for preoperative planning. In this work, we successfully develop a Deep Learning algorithm to segment the vessels within the region of interest for breast reconstruction. Ultimately, this information will be used to determine the optimal reconstructive method (choice of vessels, extent of the free flap/harvested tissue) to reduce intra- and postoperative complication rates.

Introduction

Over 250,000 new cases of invasive breast cancer are recorded in US women every year, and 58% of women in a late stage of breast cancer choose to have a mastectomy (Cancer.org 2020). Breast reconstruction is a common way to restore the quality of life of these women after a mastectomy. Among the women who undergo a mastectomy, 42% elect to undergo breast reconstruction. Breast reconstruction with free autologous tissue like the deep inferior epigastric perforator (DIEP) flap has become very popular over the last twenty years and is regarded as the first choice in the current state-of-the-art autologous breast reconstruction by many surgeons. The DIEP flap is preferred to other methods because it can provide natural results comparable to native breast tissue, and it can improve the abdominal contour without needing to weaken the abdominal wall. However, the breast reconstruction with a DIEP flap is far from being regarded as a simple surgery. The execution of this operation requires lengthy training and experience as the surgeon has to deal with unpredictable vascular patterns that supply the desired flap. Furthermore, the extent of tissue that may be harvested for transfer based on the feeding vessels is determined in the operating room per the surgeon's experience and "gut feeling". A successful microsurgery involves frequent "guessing" and requires technical versatility in overcoming challenging anatomical variations. It also requires extensive planning, usually by the means of CT (computed tomography) angiography to identify the vessels suitable for flap harvest. Presently, there is no quantitative evaluation involved, and the preoperative planning depends heavily on the experience of the responsible surgeon. The surgeon looks at the CT scan and draws from experience to plan the operation by guessing the chances of success. Our proposed technology is unique because it takes the guesses out of the equation when a surgeon is planning an operation.

Research Goal

Past work by Hembd et al. (2018) has shown that vessels which are larger in diameter are more likely to result in successful operations. However, there is no standard way to identify a vascular tree which would reliably correlate with the optimal extent of the flap harvest. The specific aim of the work is to utilize Deep Learning to segment the desired DIEP vessels within the region of interest, with the ultimate goal of computing vessel characteristics to determine the optimal reconstructive method.

Methodology

Project Workflow. For this project, we will develop and train a Deep Learning algorithm to segment the rectus abdominis muscle from the full CT scan. This muscle segmentation will be used to select the appropriate region of interest (ROI) in the CT scan for targeted vessel segmentation. Subsequently, we will train a Deep Learning algorithm to segment the vasculature of deep inferior epigastric perforators

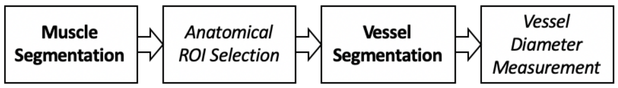

Figure 1. Project Workflow Diagram (Deep learning tasks in bold, computer vision tasks in italics)

based on expert manual CT-scan annotations from a radiologist. Once the vessels have been segmented, the vessel diameter will be measured using computer vision techniques.

For initial experiments, we focused on training the vessel segmentation model. Before training, the CTs were preprocessed, and the region of interest was manually selected.

Dataset. The vessel segmentation deep learning model was trained on the synthetic vessel dataset generated by Tetteh et al. (2020). This dataset was generated using an algorithm that simulates vascular trees using a process inspired by the biology of angiogenesis (formation of new blood vessels). The algorithm was used to produce physiologically plausible vascular trees, which can then be used for training models. Since this was a feasibility pilot study, a smaller subset of the dataset was used for faster iteration to identify the best architecture, loss function, and hyperparameters. This network was developed using a dataset of 28 cases (the dataset was split into train and validation sets) and evaluated on a held-out test set of 14 cases. Each case was split into patches of size 64 x 64 x 64 pixels, and the model was trained to classify each individual patch.

Model Architecture. For this project, initially a standard U-net architecture was used, which is the most widely used one for image segmentation in medical imaging. This architecture is especially good at learning from a relatively small dataset. In addition, a simple FCN (fully convolutional network) was trained for comparison. This network has four convolutional layers and a sigmoid classification layer with no down-sampling and up-sampling layers. This architecture was shown to be successful for vessel segmentation by Tetteh et al. (2020) because the task involves fine detailed objects which are lost with down-sampling.

Results and Discussion

A deep learning model was successfully developed and trained to segment vessels automatically in synthetic images of vessel trees. The U-net model's sensitivity and specificity on the test set were 0.938 and 0.997, respectively. The FCN model's sensitivity and specificity on the test set were 0.9988 and 0.9996, respectively. This suggests that the FCN architecture is more suited for our vessel segmentation task. The high sensitivity and specificity on the held-out test set suggest that the model is generalizing well even when trained on a small dataset.

Since the samples used to train this model are synthetic, the next step is to use transfer learning to fine-tune this model on real images. The hope is that pre-training a model on the synthetic images helps the model learn features associated with vessel structures, so it will perform better when given real cases that may be more complex. Once we get accurate vessel segmentations, we can then use the segmentations to extract quantitative vessel characteristics (e.g. the diameter and number of branching points) that can guide surgical decisions.

We are also currently working on the muscle segmentation step with a similar deep learning approach (using U-net and FCN) to complete the pipeline and automatically select the appropriate ROI for vessel segmentation.

Implications/Significance

Having an algorithm that can predict the optimal reconstructive method will help reconstructive surgeons to better inform the patient pre-surgery which surgical procedure will be carried out. The algorithm would also simplify decision making and standardize the approach, so less experienced surgeons can perform DIEP reconstruction safely.

Breast reconstruction is just one very frequent microsurgical example. By knowing the key to the individual vascular pattern of the patient, this technology has the potential to be extrapolated to any free tissue transfer reconstruction in a very personalized way. Ultimately, a user-friendly software based on this algorithm would be developed, which can then be commercially distributed to microsurgical reconstruction centers. The long-term goal of this project is to improve planning, outcomes, and safety of any microsurgical procedure. This approach has the potential to considerably shorten operating times and lower healthcare costs.

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