3D rendering and analysis of dermal backflow as an early indicator of cancer-acquired lymphedema using RGB-D and Near-infrared fluorescence lymphatic imaging

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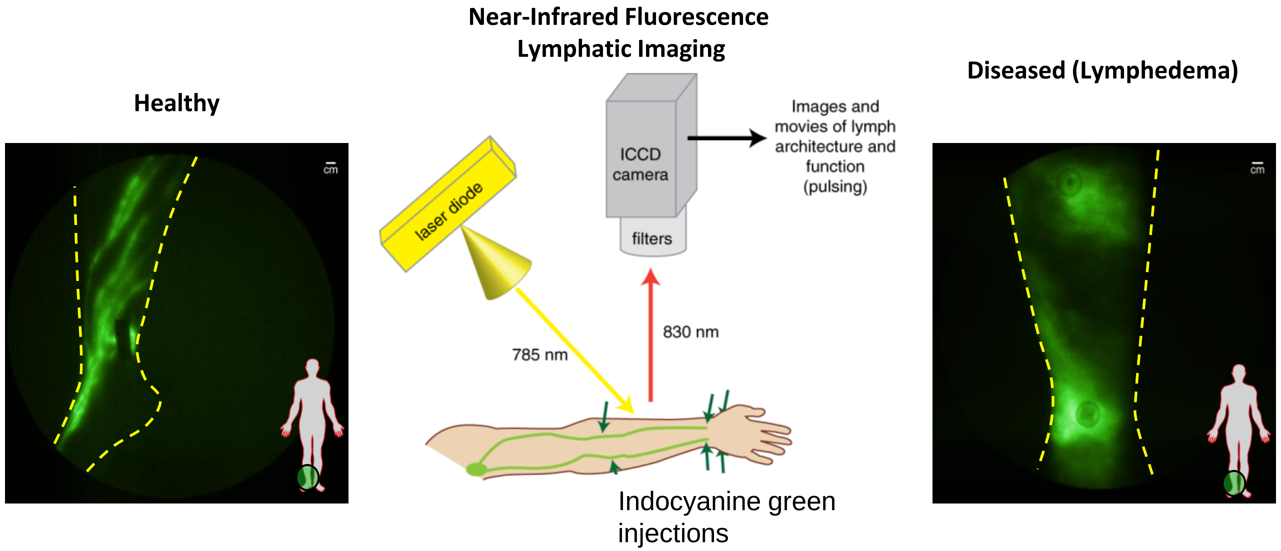
Cancer-acquired lymphedema

- Lymphatics are essential in cardiovascular health and immune surveillance but are often medically overlooked.
- Cancer-acquired lymphedema (LE) is a common, incurable sequelae of cancer treatment in the growing population of cancer survivors.
- Dermal backflow (DBF), which refers to lymphatic reflux due to lymphatic valve insufficiency, is a diagnostic finding in lymphedema.

Lymphatic architecture imaging

- To image and characterize healthy and diseased lymphatic architecture, near-infrared fluorescence (NIRF) lymphatic imaging techniques with indocyanine green (ICG) as a contrast agent are used.



Schematic of the NIRF lymphatic imaging system (center) and example images [1] of healthy lymphatics (left) and diseased lymphatics (right).

- Currently, the diagnostics to detect early changes in lymphatic function or any curative treatments for LE remain limited.

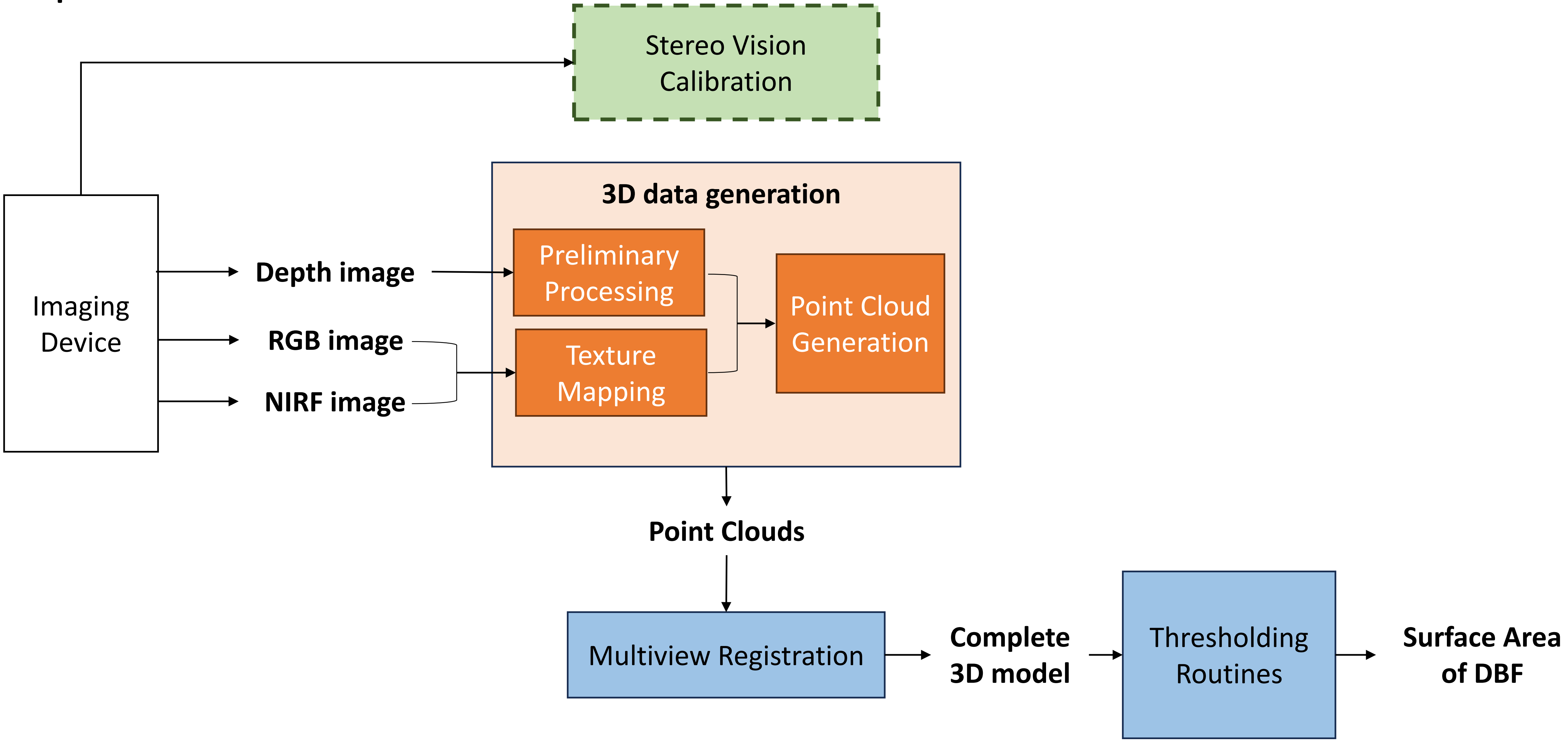
1. O'Donnell, *et al.*, J. Vasc. Surg. Venous. Lymphat. Disord. 5(2):261-271, 2017 (PMID: 28214496).

Objective

- Visualize and understand dermal backflow as an early indicator of LE using NIRF lymphatic imaging.

- Quantitate lymphatic dysfunction in breast-cancer related lymphedema.

Pipeline Overview



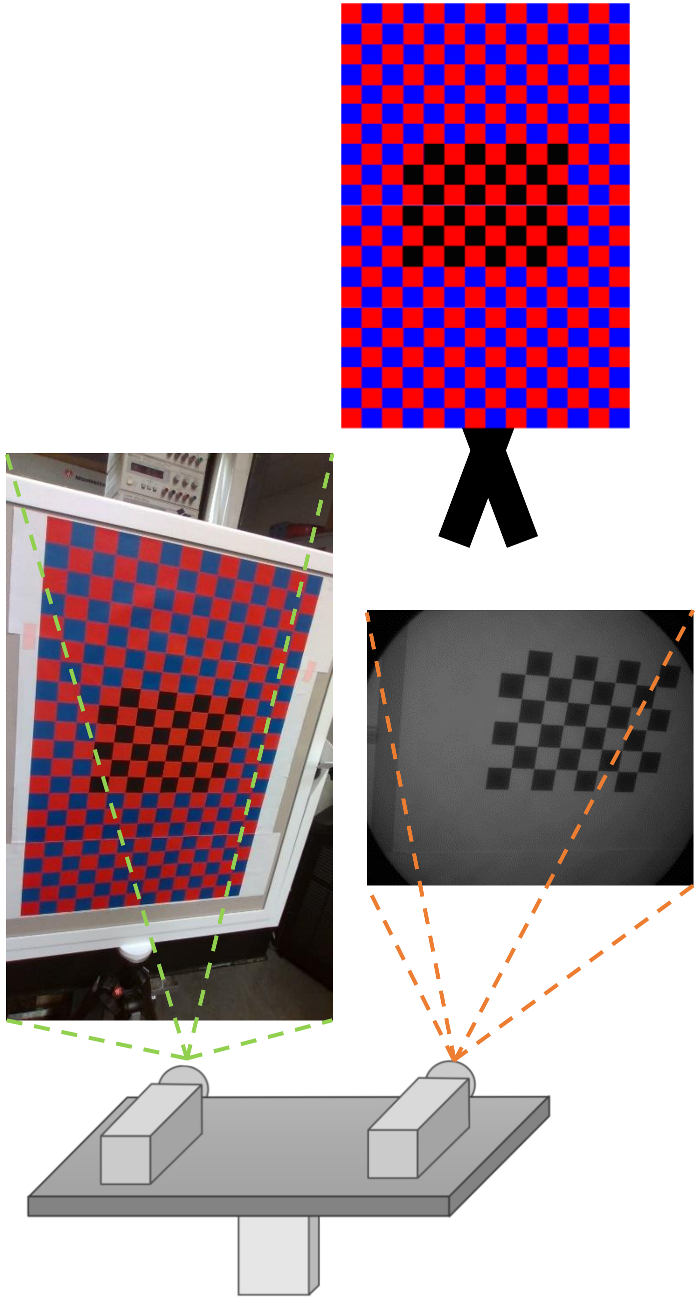
Instrumentation

- The set up consists of two cameras mounted side by side on a mobile mechanical arm.
  - RGB-D camera from Intel RealSense.
  - Near-Infrared Fluorescence (NIRF) camera.

- The geometric relationship between the object being imaged and the imaging system is defined.

Stereo Vision Calibration

- Stereo camera calibration aims at finding the relative pose of a camera with respect to a second camera.
  - RGB camera to Depth camera
  - **NIRF camera to RGB camera**
- The NIRF and RGB cameras have different fields of view (FoV) where the widest corresponds to the latter.



Stereo Vision Calibration

- We perform mono camera calibration on each camera to acquire the intrinsic and extrinsic matrices relative to the real world.

$$P_{Image} = K[R|t]\ P_{World}$$

Where K is the intrinsic matrix of the camera, [R|t] is its extrinsic matrix, R denotes the 3×3 rotation matrix, and t denotes the 3×1 translation vector.

Stereo Vision Calibration

- The stereo calibration is performed using transformation matrices due to the cameras different FoVs.
- To find the relative pose of the NIRF camera with respect to the RGB camera we used the following equation:

$$\boldsymbol{T_{CF}} = \boldsymbol{T_{WC}^{-1}} \times \boldsymbol{T_{WF}}$$

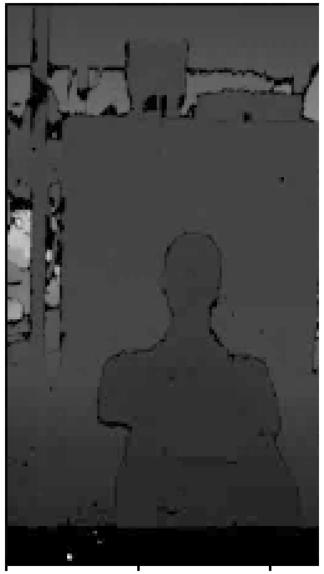
$$T_{WC} = [R|t]_{WC}$$

$$T_{WF} = [R|t]_{WF}$$

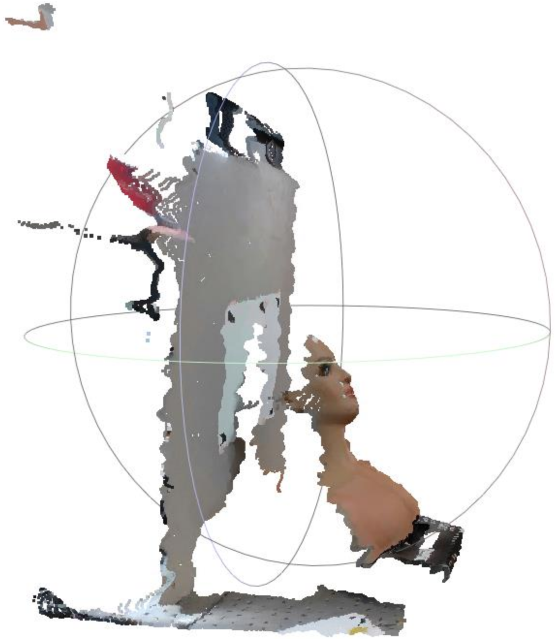
Where T_{WC}, T_{WF}, T_{CF} are the transformation matrix of the RGB camera relative to world coordinates, the NIRF camera relative to the world coordinates, and the NIRF camera relative to the RGB camera, respectively.

Preliminary processing

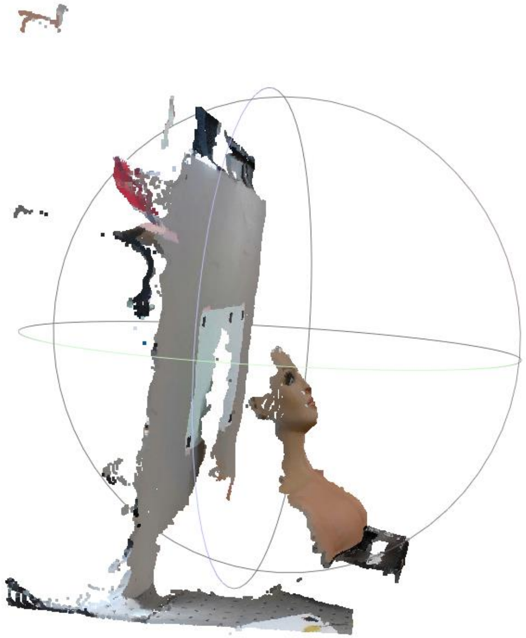
- Depth map filtering
  - An edge preserving temporal filter is applied to a sequence of depth frames to improve the depth map quality.
  - Depth frames averaging is computed using an Exponential Moving Average.



Raw depth map



Point cloud generated from raw depth map



Point cloud generated from a depth map smoothed with temporal filtering.

3D coordinates acquisition from the depth image

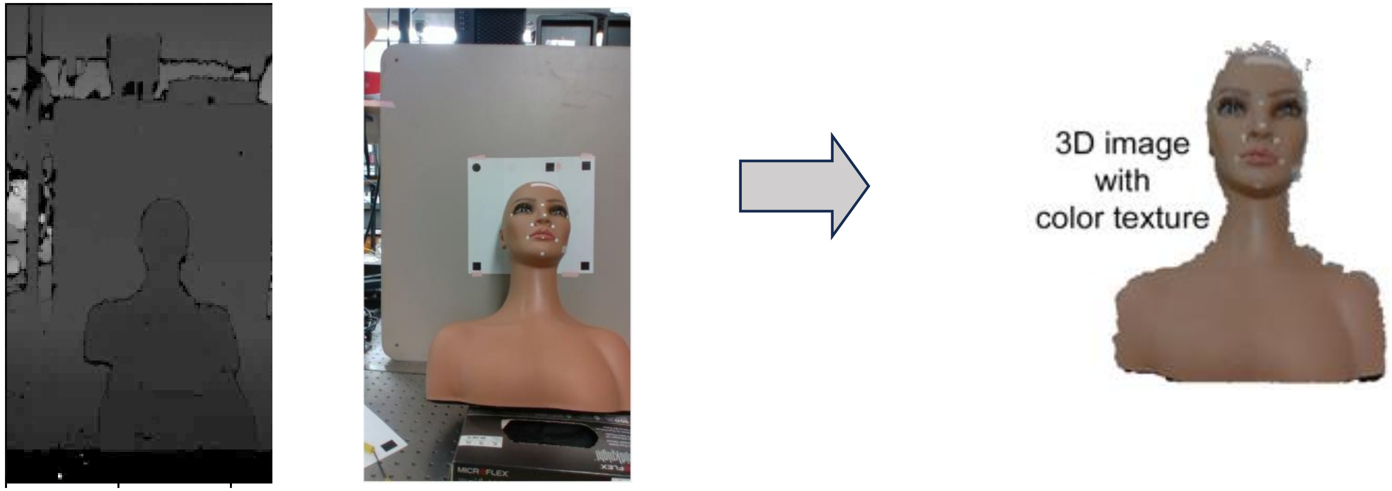
- We compute the point cloud using the depth image and the depth camera intrinsic matrix.
- The depth image is a matrix of size 848 × 480 where each pixel is a 16-bit integer that represents the distance in millimeters.
- We use the following formula to transform the depth pixels from the depth image 2D coordinate system to the depth camera 3D coordinate system (x, y and z):

$$\begin{cases} z = depth(i,j) \\ x = \dfrac{(j - c_x) \times z}{f_x} \\ y = \dfrac{(i - c_y) \times z}{f_y} \end{cases}$$

Where $depth(i,j)$ is the depth value at the row i and column j. f_x, f_y and c_x, c_y are the focal length and the optical centers, respectively.

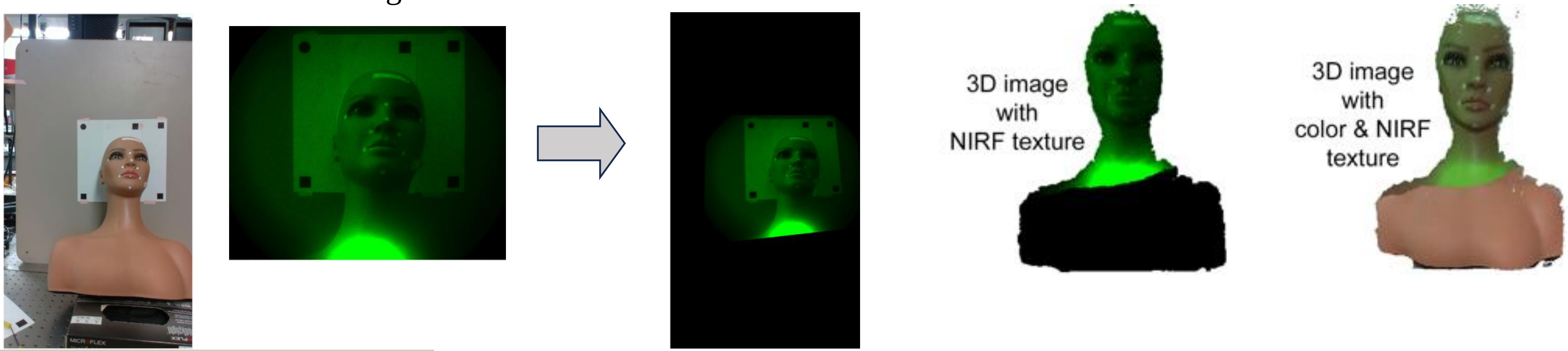
Color texture mapping

- **Objective**: Create a real-world color texture map corresponding to the generated point cloud.
- **Method**:
  - Transform the point to the RGB camera coordinate system using the RGB camera to Depth camera extrinsic matrix.
  - Map the transformed point to the color image coordinate system.
  - Assign the color value of the mapped pixel in the 2D color image to the corresponding location within point cloud.



NIRF texture mapping

- **Objective**: Create a NIRF texture map corresponding to the generated point cloud.
- **Method**:
  – Convert the fluorescent image to color image space using the computed NIRF to color extrinsic matrix.
  – Each pixel indices from color texture mapping phase is used as coordinates to locate corresponding NIRF texture pixel.
  – Assign the color value of the located pixel within transformed NIRF image to corresponding location within point cloud.
  – A green pseudo color is applied to greyscale NIRF images for visualization, particularly when overlaid on RGB images



Multiview Registration

- Image registration is a process for determining the correspondence between images collected at different times or using different imaging modalities.
- Two types of registration:
  - Rigid registration.
  - Non-rigid registration.

- **Objective**:
  - Combine different perspectives from the imaged subject with acquired 3D data into a single model.

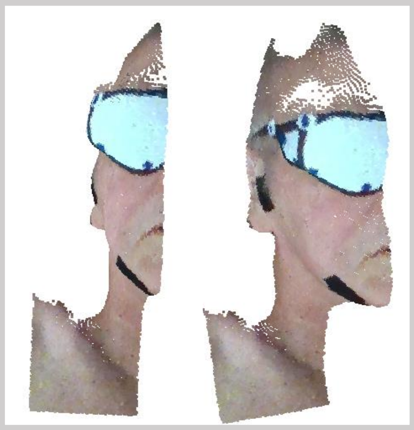
Multiview Registration

- Acquire point clouds from five different views of a target.
- Manually locate fiducial points in each point cloud.

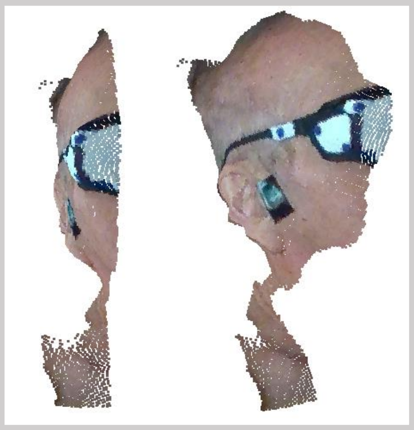
Right view 90 degrees | Right view 45 degrees | Frontal view | Left view 45 degrees | Left view 90 degrees

Multiview Registration

- Pre-align the lateral point clouds using the fiducials.
- Apply the Iterative Closest Point algorithm (ICP) to improve the alignment.

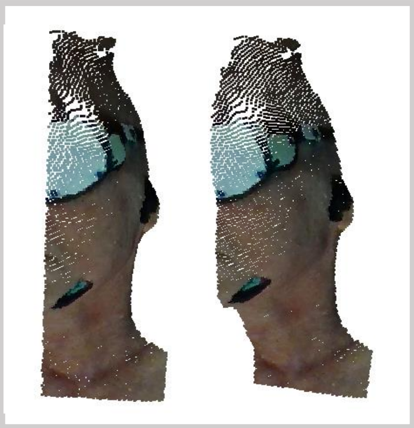


Right view 45 degrees



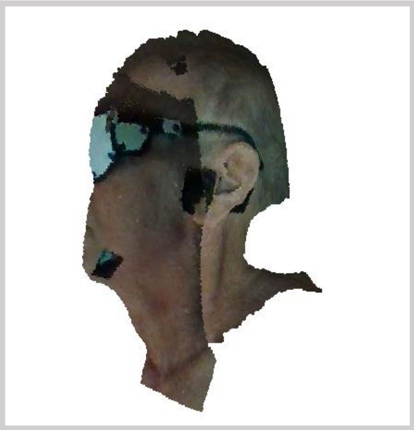
Right view 90 degrees

Complete Right view



Left view 45 degrees

Left view 90 degrees



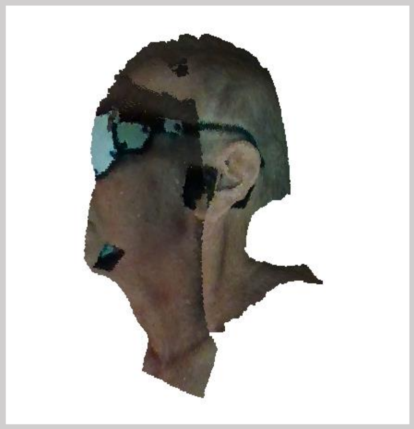
Complete Left view

Multiview Registration

- Align lateral view and frontal view point clouds.
- Create a complete 3D model of the subject head and neck.


Complete Right view


Frontal view


Complete Left view


Complete view

Thresholding routines – 2D images

- **Objective**: Segment the dermal back flow in NIRF images to quantify its spread.
- **Method:** Transfer learning
  - U-Net, a convolutional neural network designed primarily for image segmentation.
- **Dataset:**

Training set	15 images
Testing set	10 images

  - We use data augmentation techniques to provide the model with new variation of the images during training.
  - The training set size increases to 60 images at each epoch.

Thresholding routines – 2D images

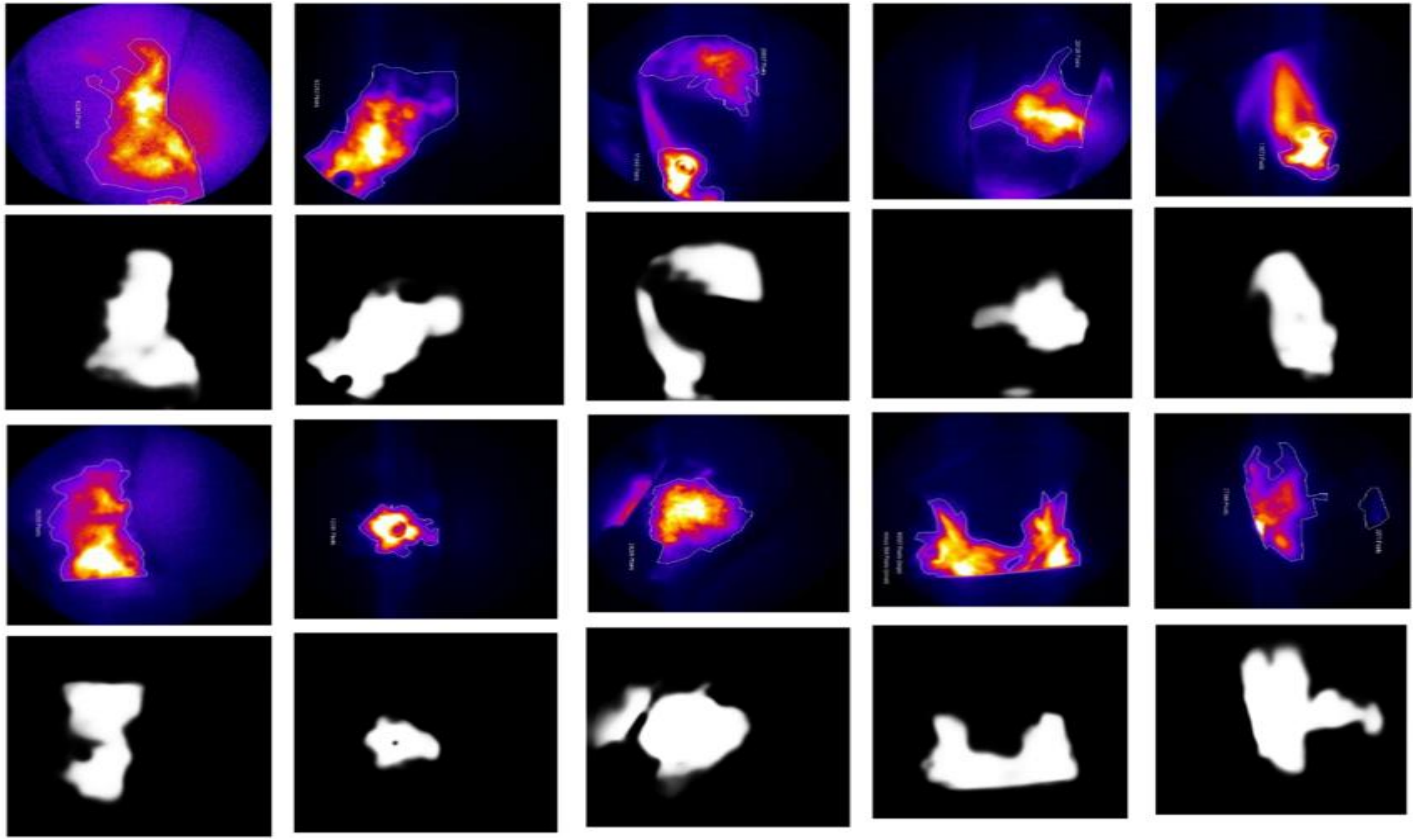
- **U-Net segmentation results (Testing set)**

Ground Truth

Segmented mask from U-Net

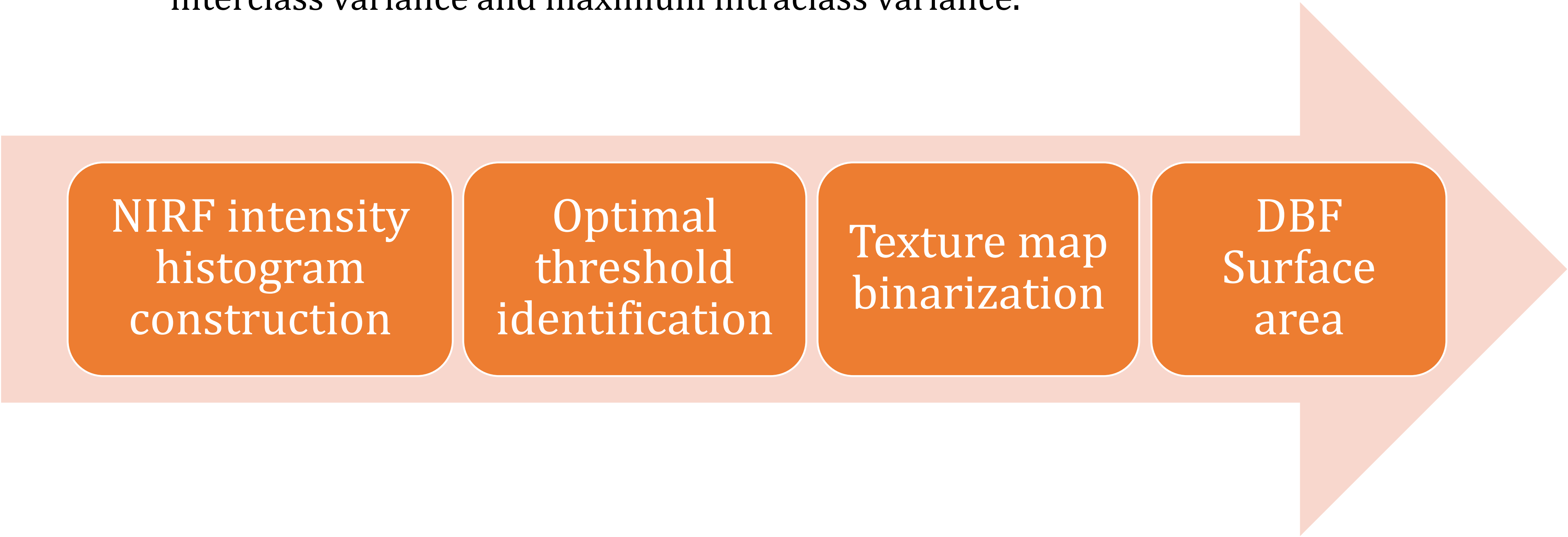
Ground Truth

Segmented mask from U-Net



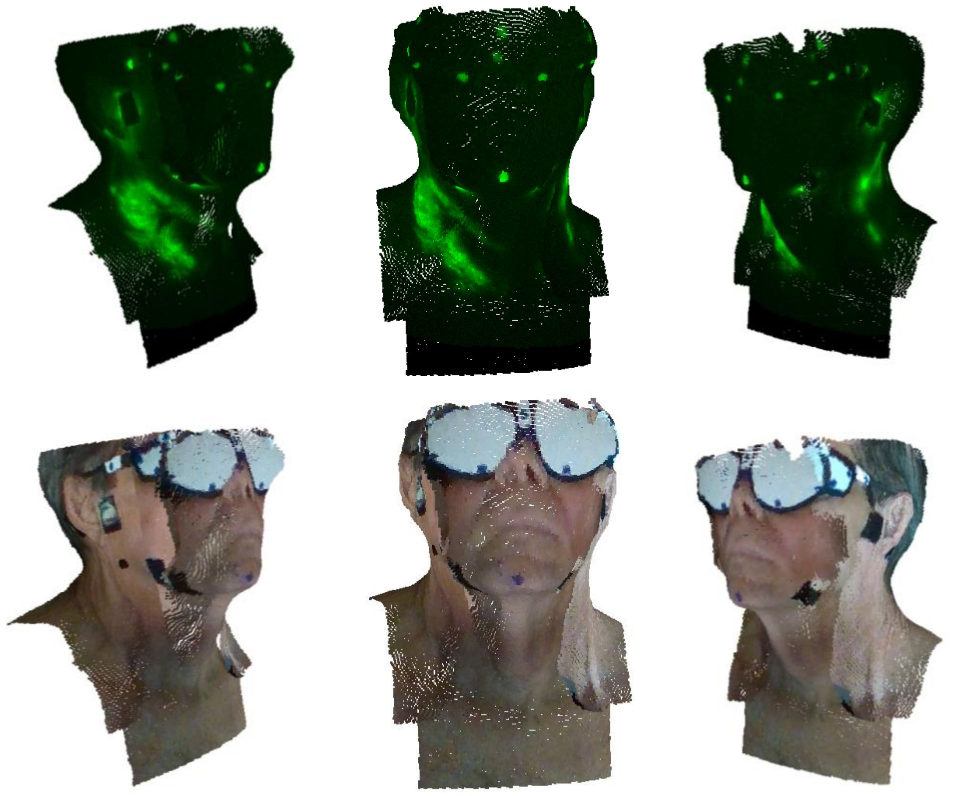
Thresholding routines – 3D images

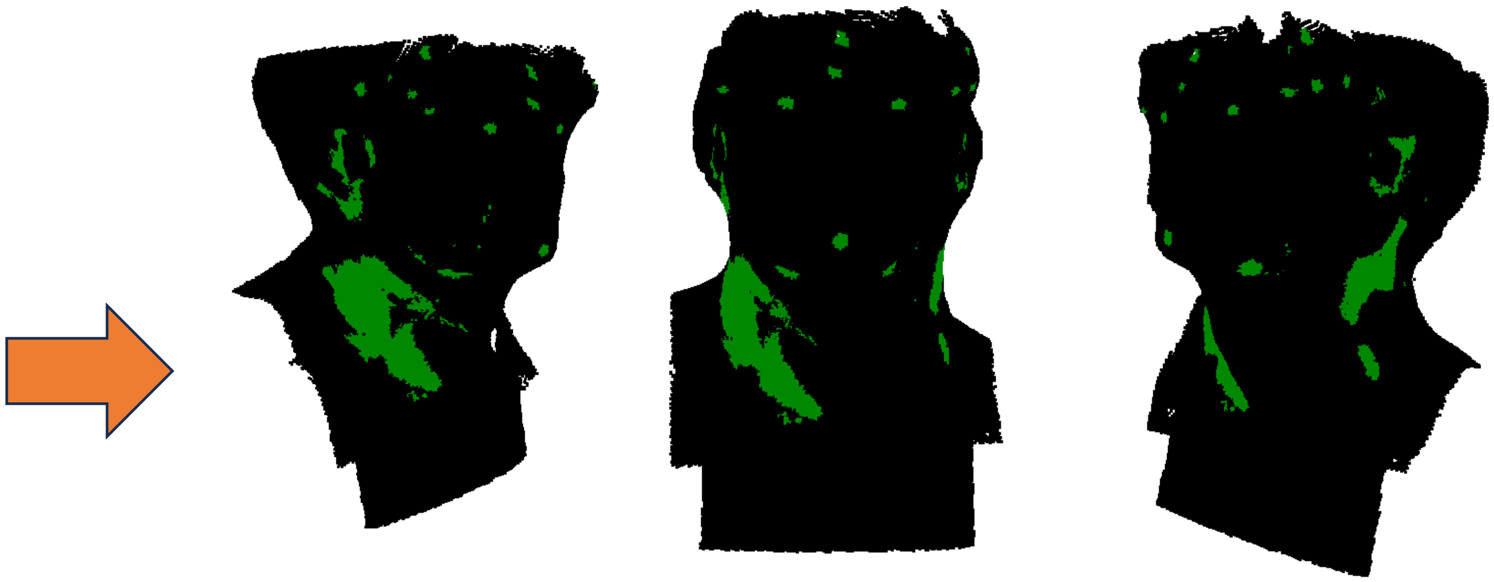
- **Objective**: Segment the dermal back flow in the NIRF texture map of a 3D model to quantify its spread.
- **Method:**
  - Adaptive thresholding of the texture map to identify a threshold value with minimum interclass variance and maximum intraclass variance.



Thresholding routines – 3D images

- Dermal backflow surface area = `107.36 cm2`

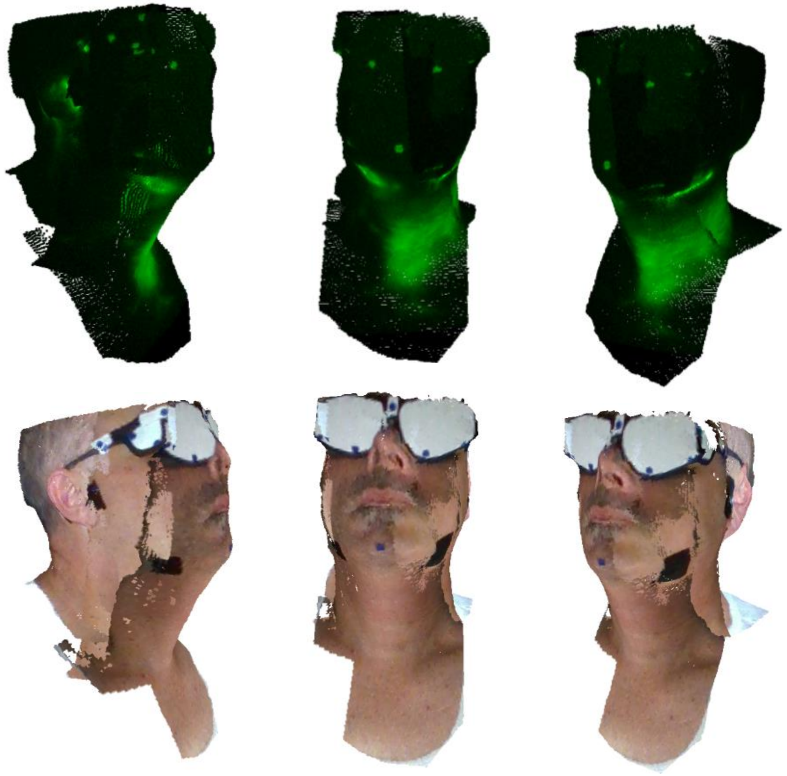


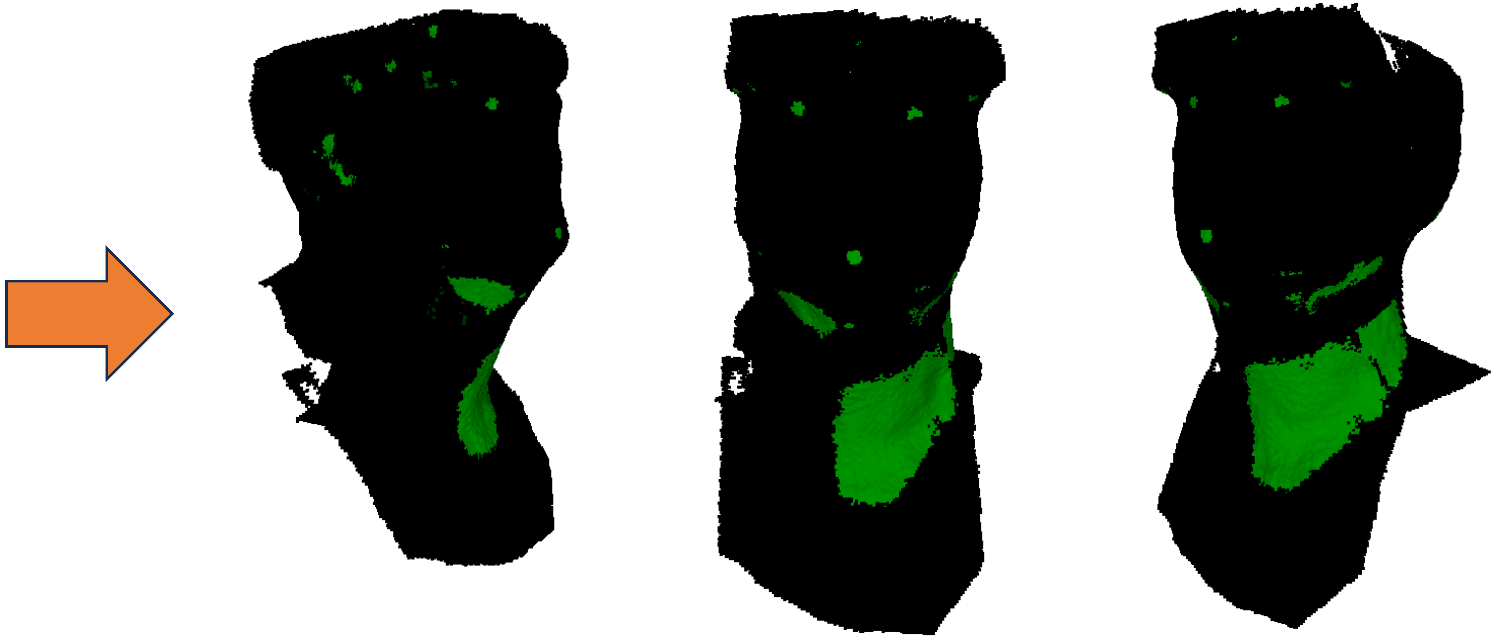


Result of thresholding the 3D mesh with NIRF texture.

Thresholding routines – 3D images

- Dermal backflow surface area = `131.45 cm2`





Result of thresholding the 3D mesh with NIRF texture.

Conclusion and Future Work

- Accurate reconstruction of 3D models with a NIRF texture overlay using data from our NIRF and RGB-D stereo camera device.

- Quantification of dermal backflow on clinically relevant 3D surfaces is feasible and may provide a clinically useful measurement of lymphatic dysfunction.

- Future work includes the further development and optimization of the described approaches and their validation in the current clinical trial.
  - Creating a smoother and more coherent skin texture of the stitched 3D mesh using color correction algorithms.
  - Exploring machine learning based approaches to segment 3D meshes with NIRF texture once we acquire sufficient data.