Automating 3D Surgical Suture Planning

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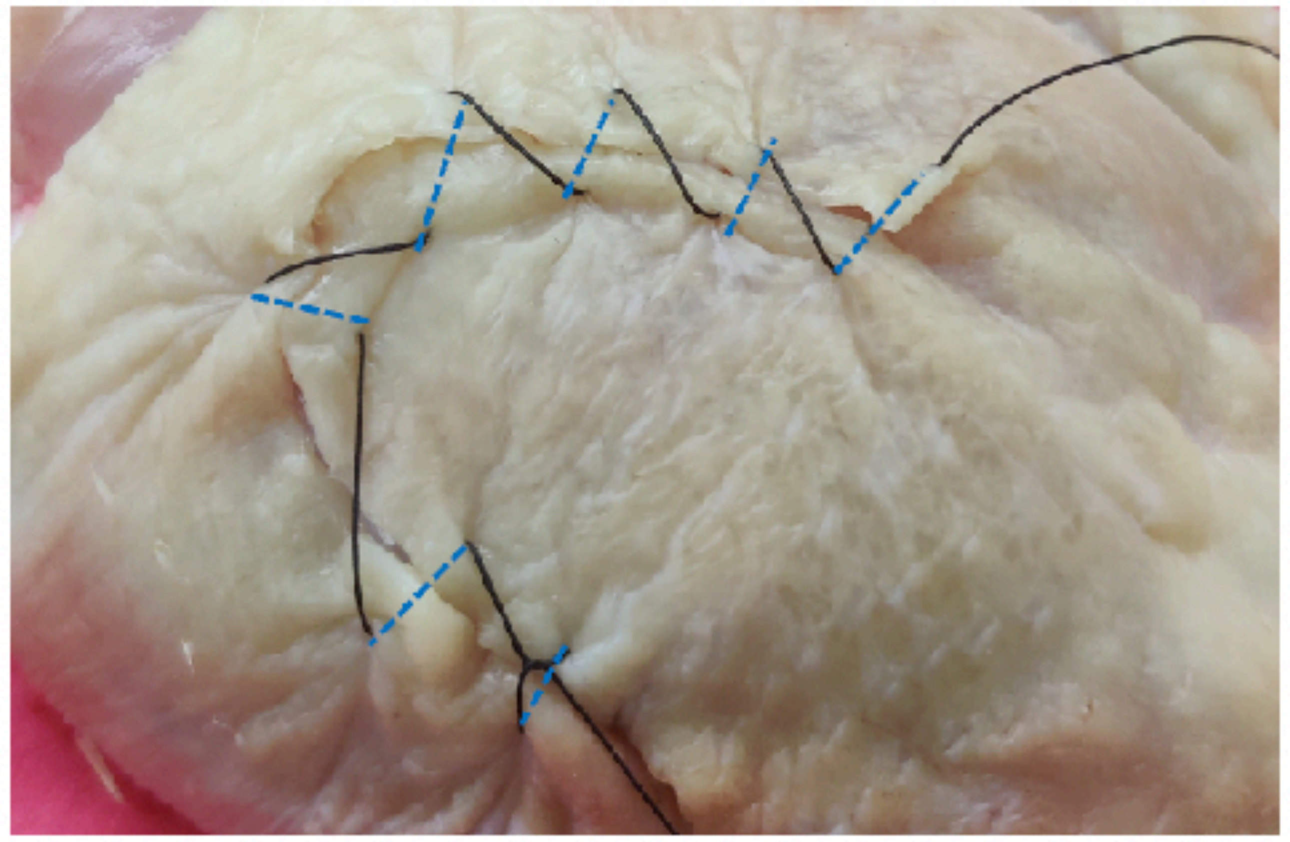
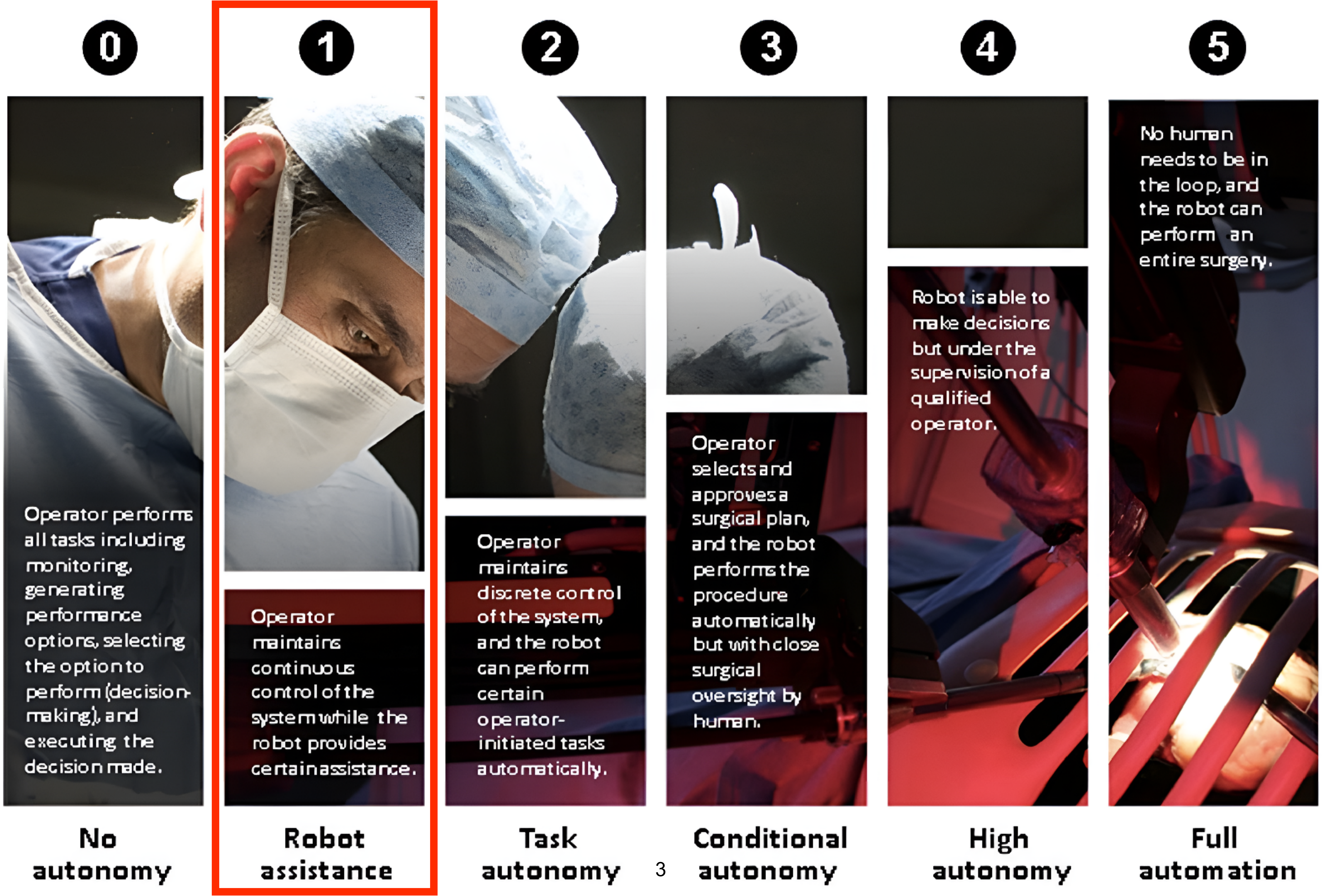
CASE 2024



* denotes equal contribution

Robot Surgery

2M robot surgeries. How many required a human surgeon?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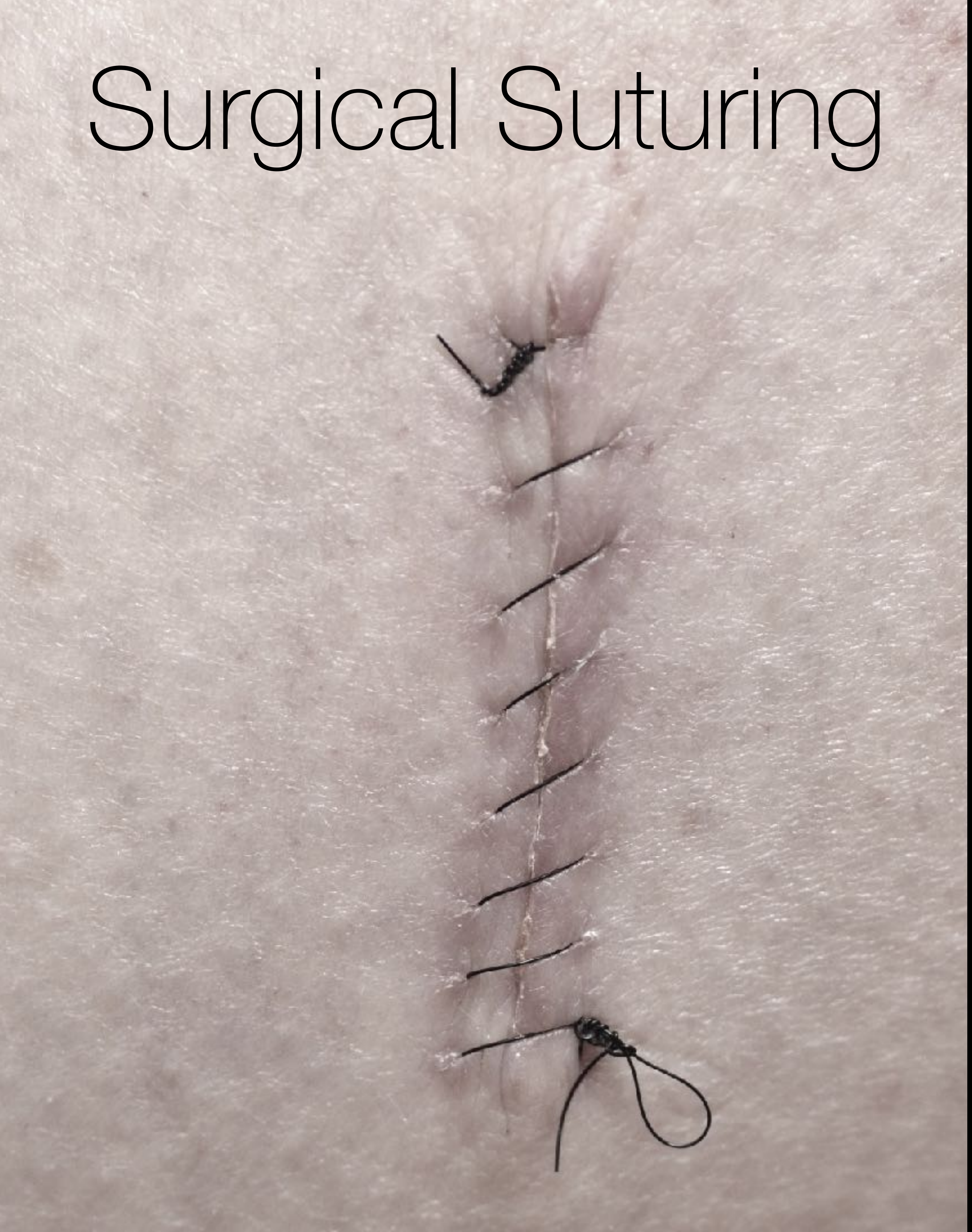
Operator performs all tasks including monitoring, generating performance options, selecting the option to perform (decision-making), and executing the decision made.
No autonomy
1
Operator maintains continuous control of the system while the robot provides certain assistance.
Robot assistance
2
Operator maintains discrete control of the system, and the robot can perform certain operator-initiated tasks automatically.
Task autonomy
3
Operator selects and approves a surgical plan, and the robot performs the procedure automatically but with close surgical oversight by human.
Conditional autonomy
4
Robot is able to make decisions but under the supervision of a qualified operator.
High autonomy
5
No human needs to be in the loop, and the robot can perform an entire surgery.
Full automation

“Augmented Dexterity”:
How Robots Can Enhance Surgeon Dexterity

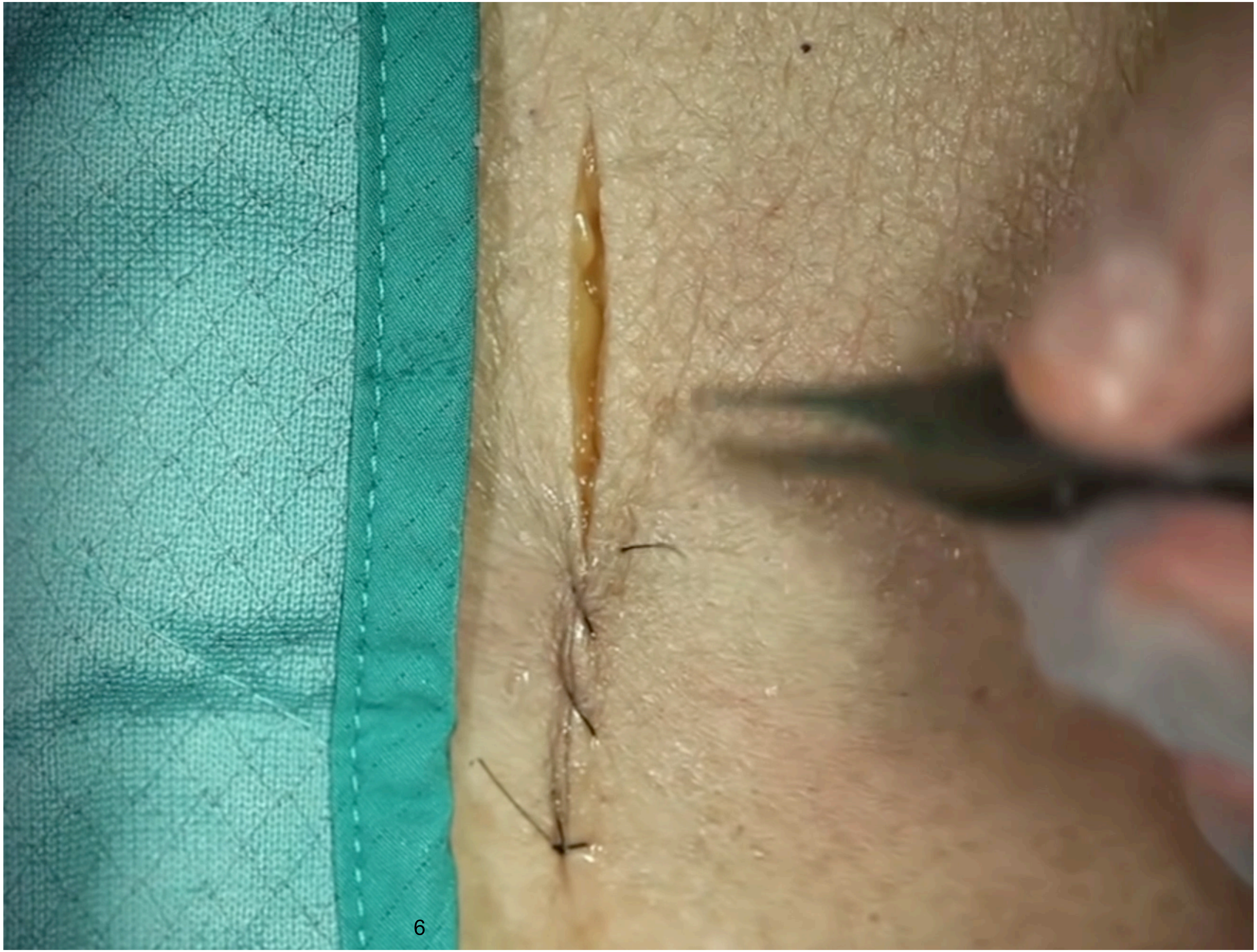
Augmented Dexterity describes systems where surgical subtasks are controlled by the robot under the close supervision of the human surgeon who is ready to take over at a moment’s notice.

K. Goldberg 2024
https://bit.ly/Augmented-Dexterity-S24

Surgical Suturing



Surgical Suturing



STITCH: Augmented Dexterity for Suture Throws Including Thread Coordination and Handoffs

Kush Hari[1]*, Hansoul Kim[1]*, Will Panitch[1]*, Kishore Srinivas[1], Vincent Schorp[1,2], Karthik Dharmarajan[1], Shreya Ganti[1], Tara Sadjadpour[1], Ken Goldberg[1]

Abstract— **We present STITCH: an augmented dexterity suturing pipeline for the dVRK surgical robot. STITCH performs needle insertion, thread sweeping, needle extraction and suture cinching, needle handover, and needle pose correction, with failure recovery policies for these actions. We introduce a novel visual 6D needle pose estimation framework using a stereo camera pair and an augmented dexterity suturing motion controller. In the augmented dexterity framework, a surgeon monitors autonomous subtasks and intervenes when either the robot or surgeon deems it necessary. We STITCH a wound phantom and compare its performance against simpler policies, including a proprioception-only and a no-visual-serviong policy. In physical experiments, we find that across 15 trials, STITCH achieves an average of 2.93 sutures without human intervention and 4.47 sutures with human intervention. See `https://sites.google.com/berkeley.edu/stitch` for code and supplemental materials.**

I. Introduction

Recent advancements in surgical robotics, like Intuitive Surgical's da Vinci Robotic Surgical Assistant (RSA), have gained popularity in operating rooms for their precision and minimally invasive capabilities. These robots aid surgeons by enhancing their range of motion and vision while reducing patient recovery time and complications. One such advancement is augmented dexterity, where the RSA assists with surgical tasks under a surgeon's supervision. This approach

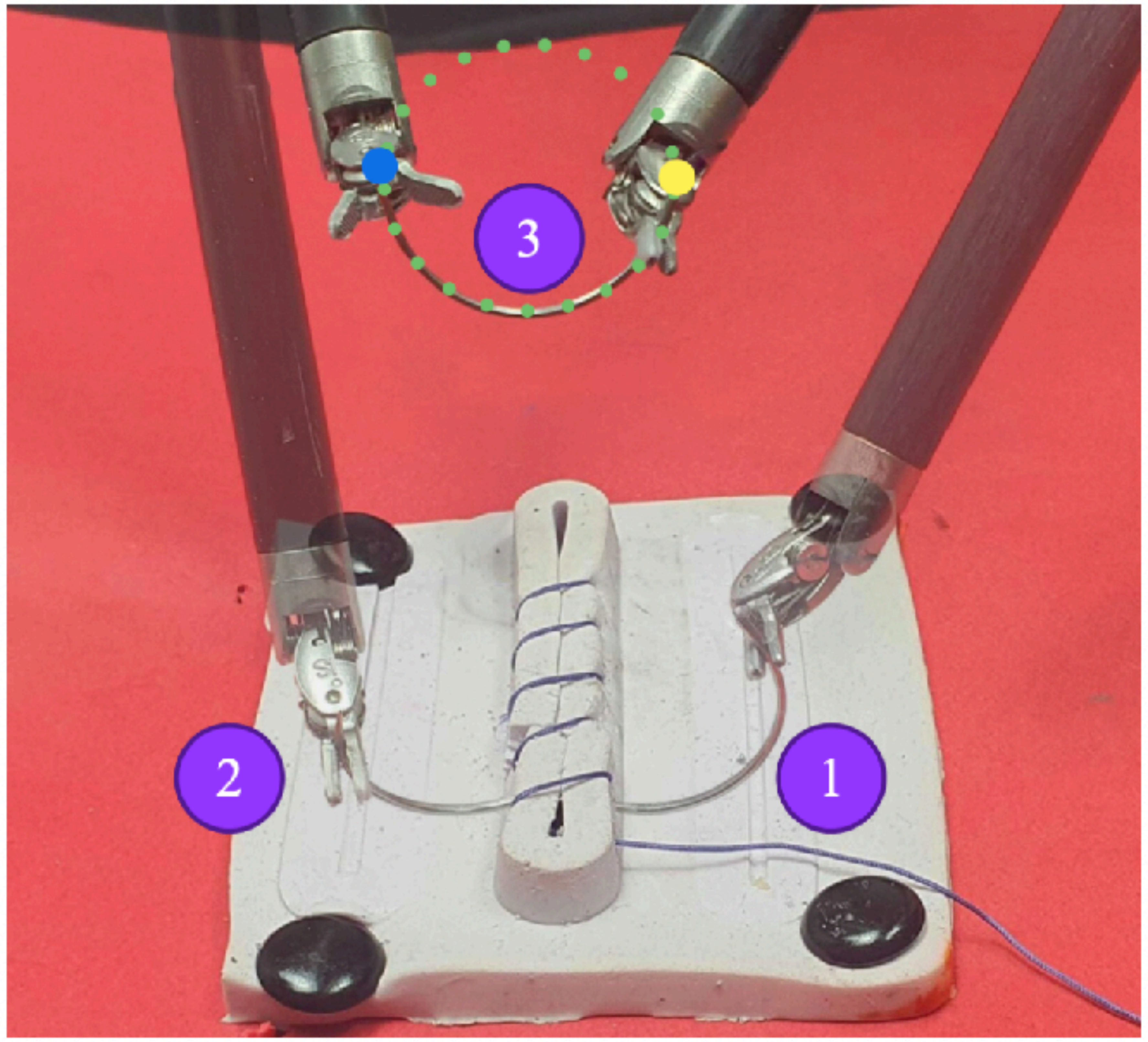
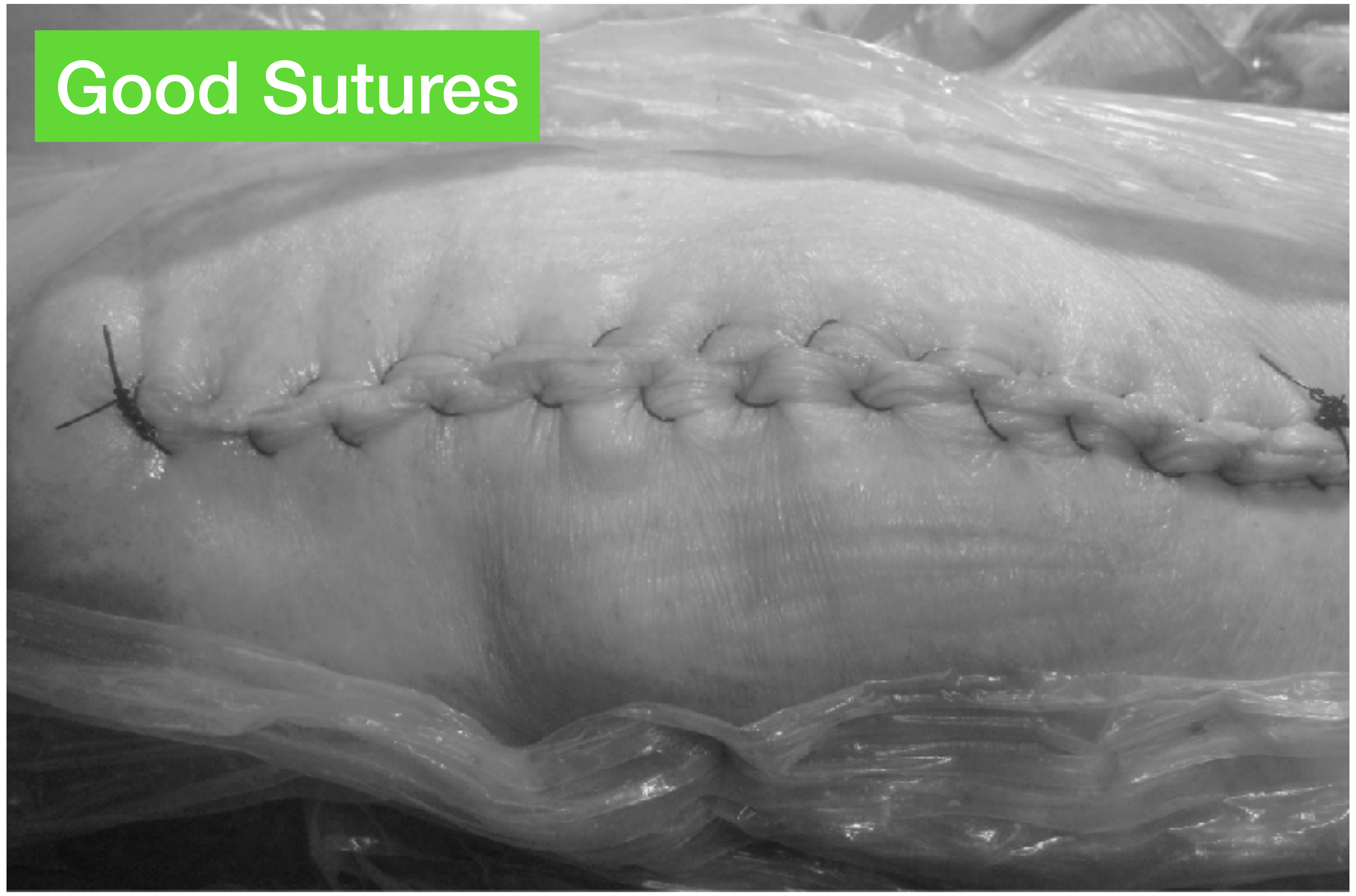
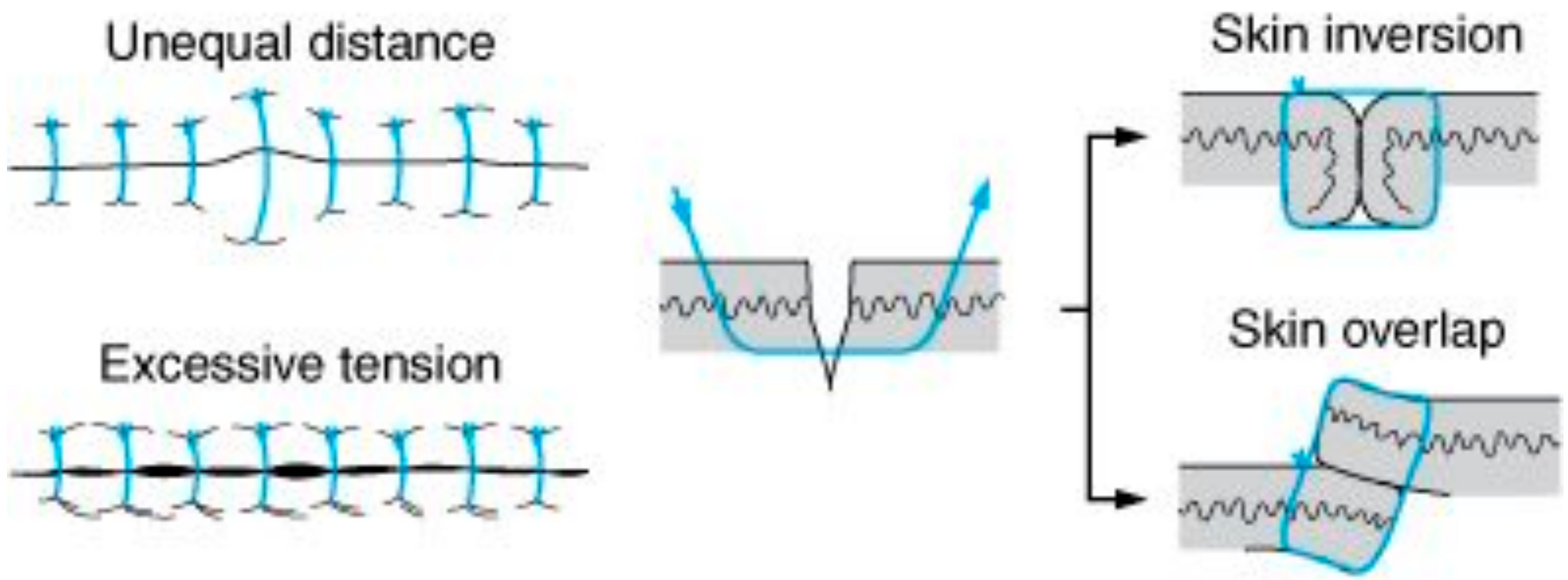
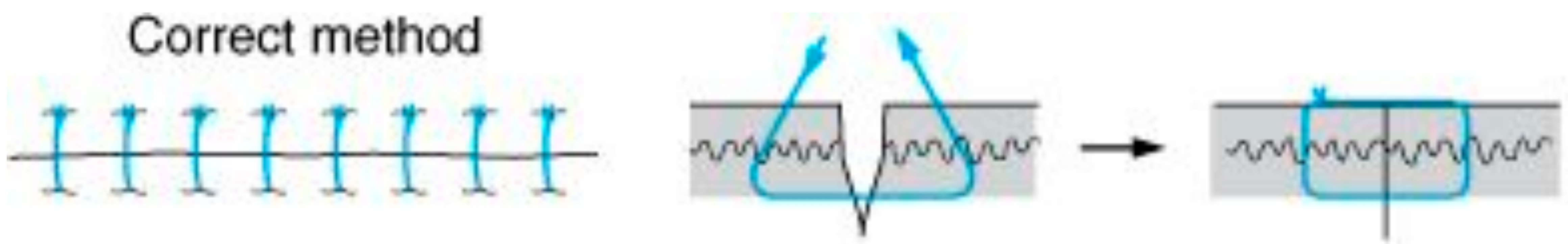


Fig. 1. **6 sutures performed by STITCH.** Step 1 shows Needle Insertion, Step 2 shows Needle Extraction, and Step 3 shows Needle Handover with Pose Correction. Detections of the needle endpoints are shown in the photo with the needle tip point shown as the blue circle and the needle swage point shown as the yellow circle. The light green circle represents the estimated needle pose.

High Quality sutures:
1) speed healing, 2) reduce risk of infection, and 3) reduce scarring

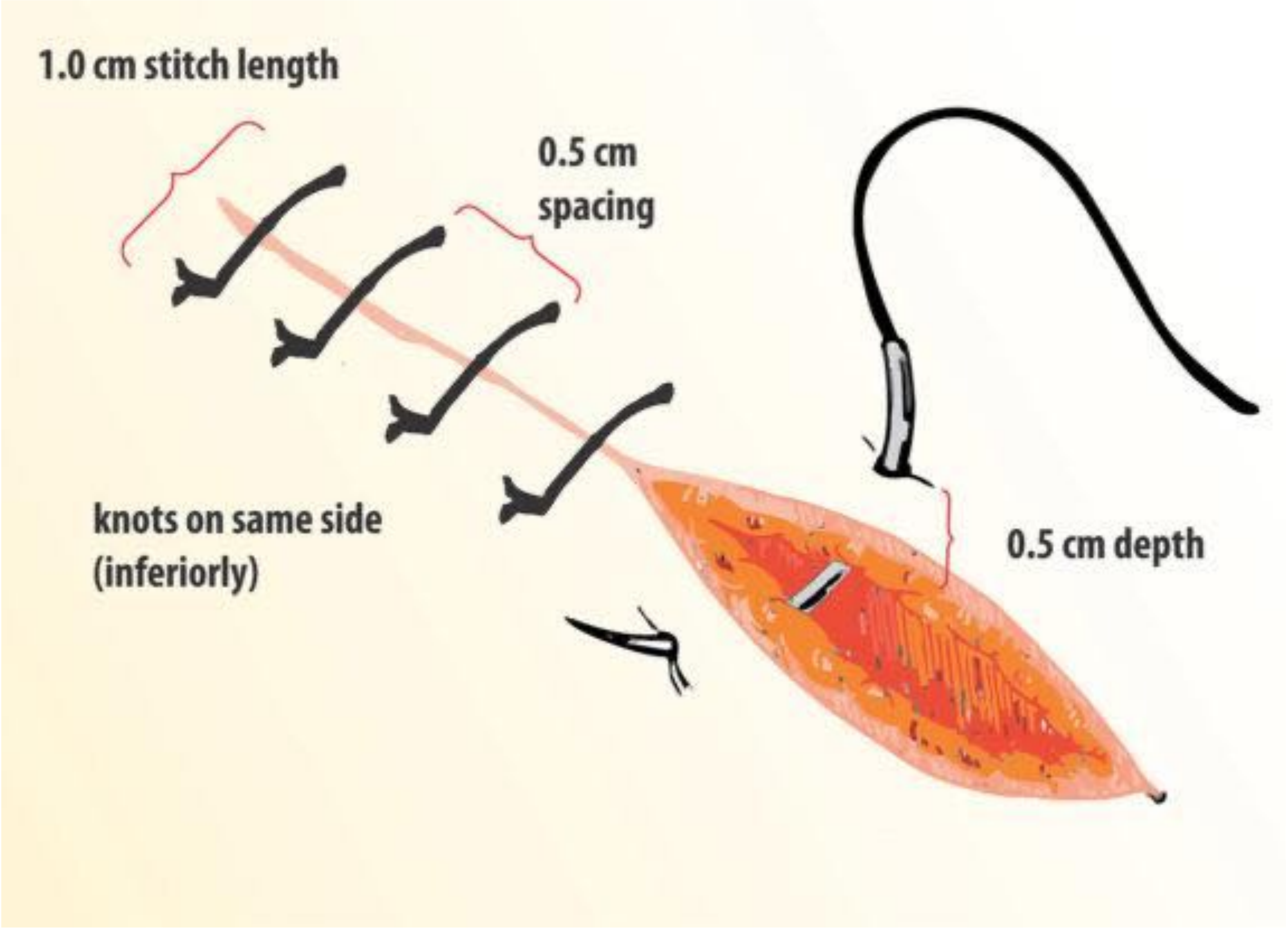






High Quality Sutures:

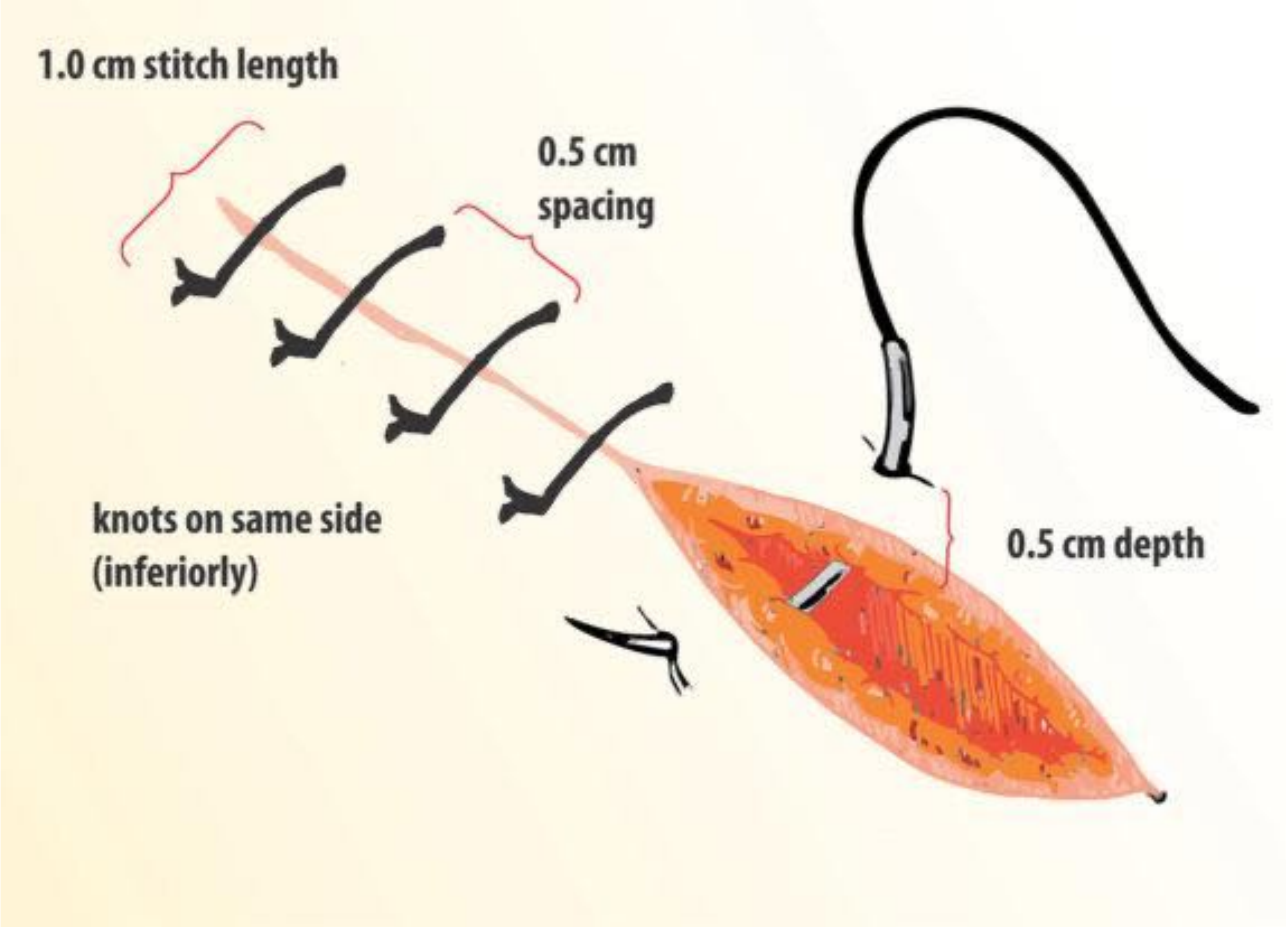
- Minimum spacing
- Uniform skin tension



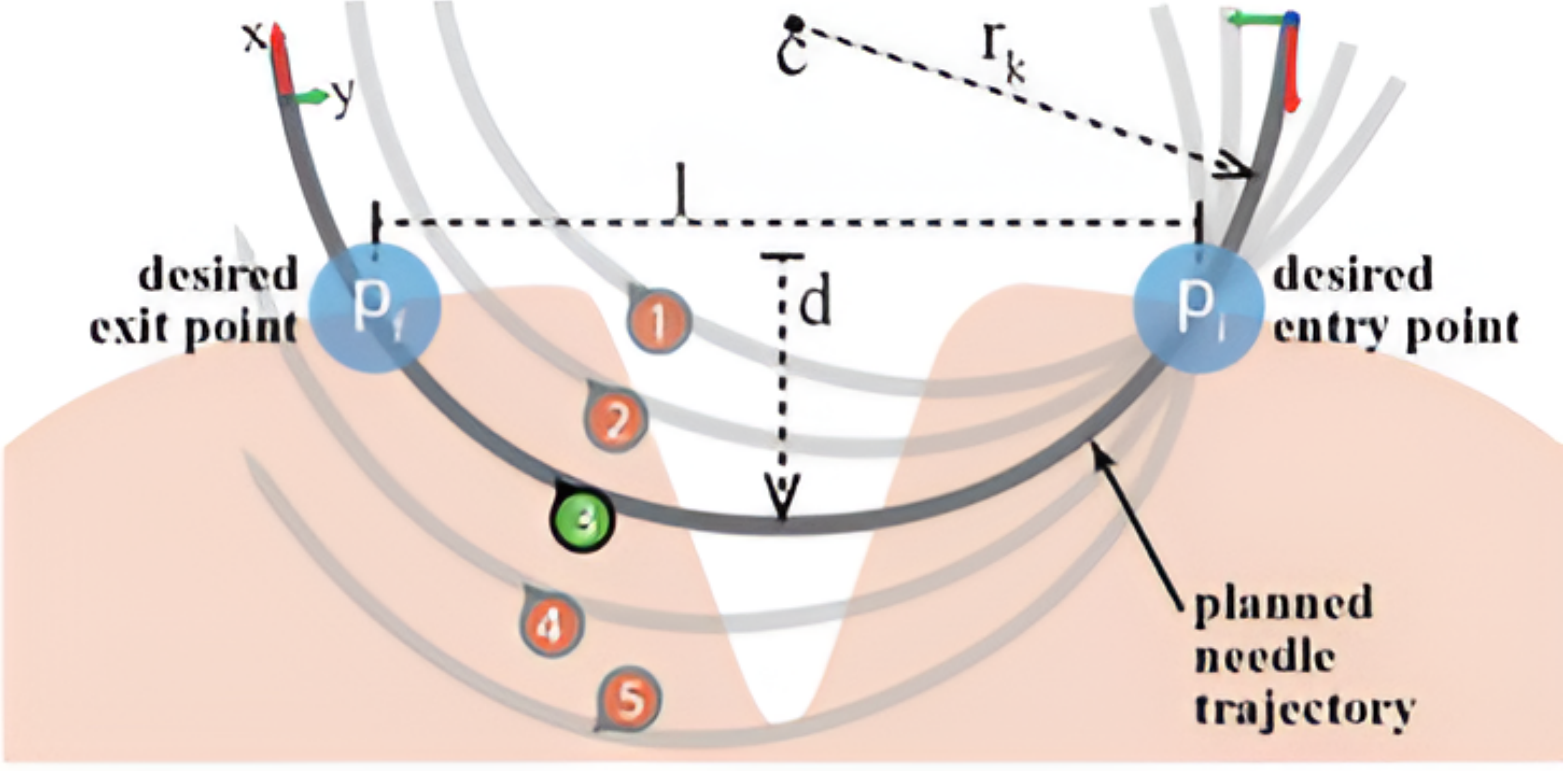
[1] General Medical Disposable, “Suturing techniques,” https://gmdgroup.com.tr/en/suturing-techniques/, 2019, Accessed Jul 2023.

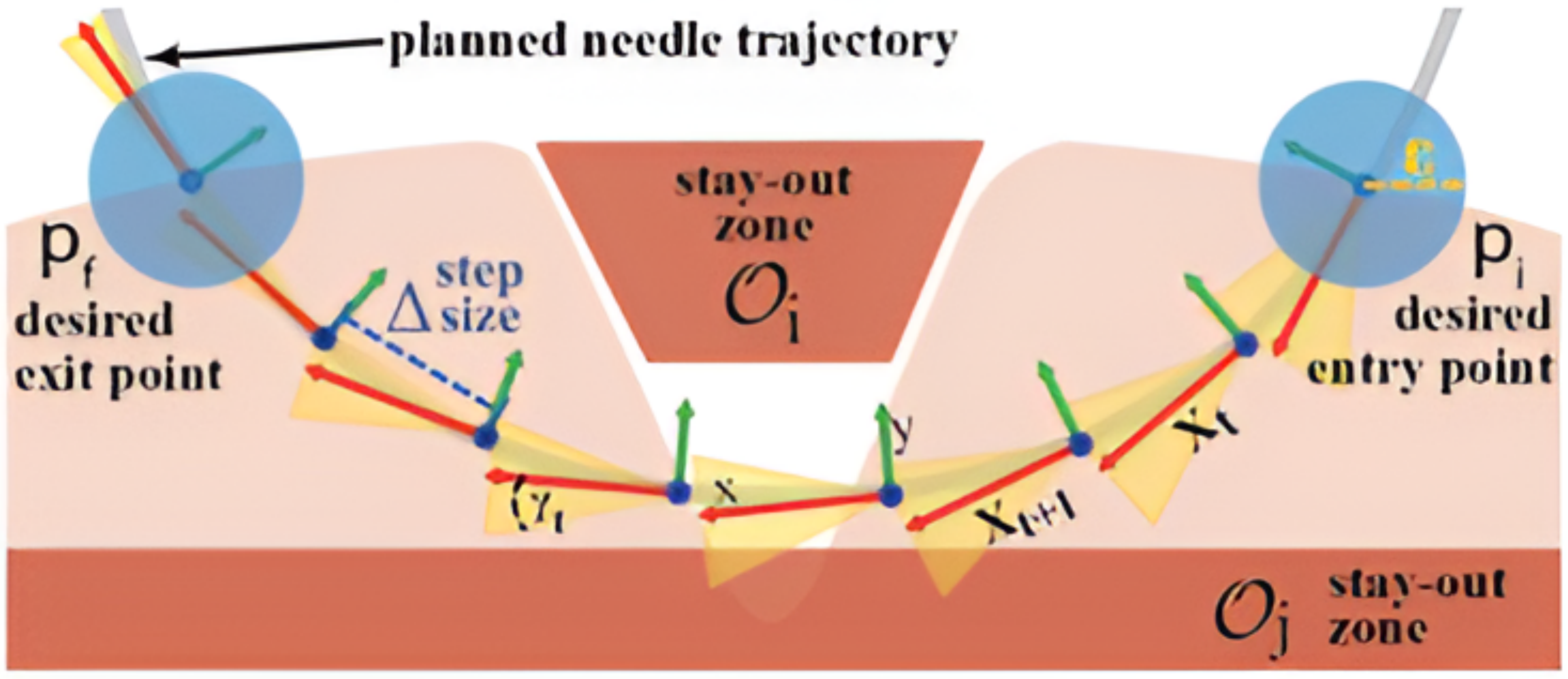
Suture Planning

Given a wound,
Compute **needle entry and exit points** that optimize factors and meet constraints



Prior Work: Needle Motion Planning

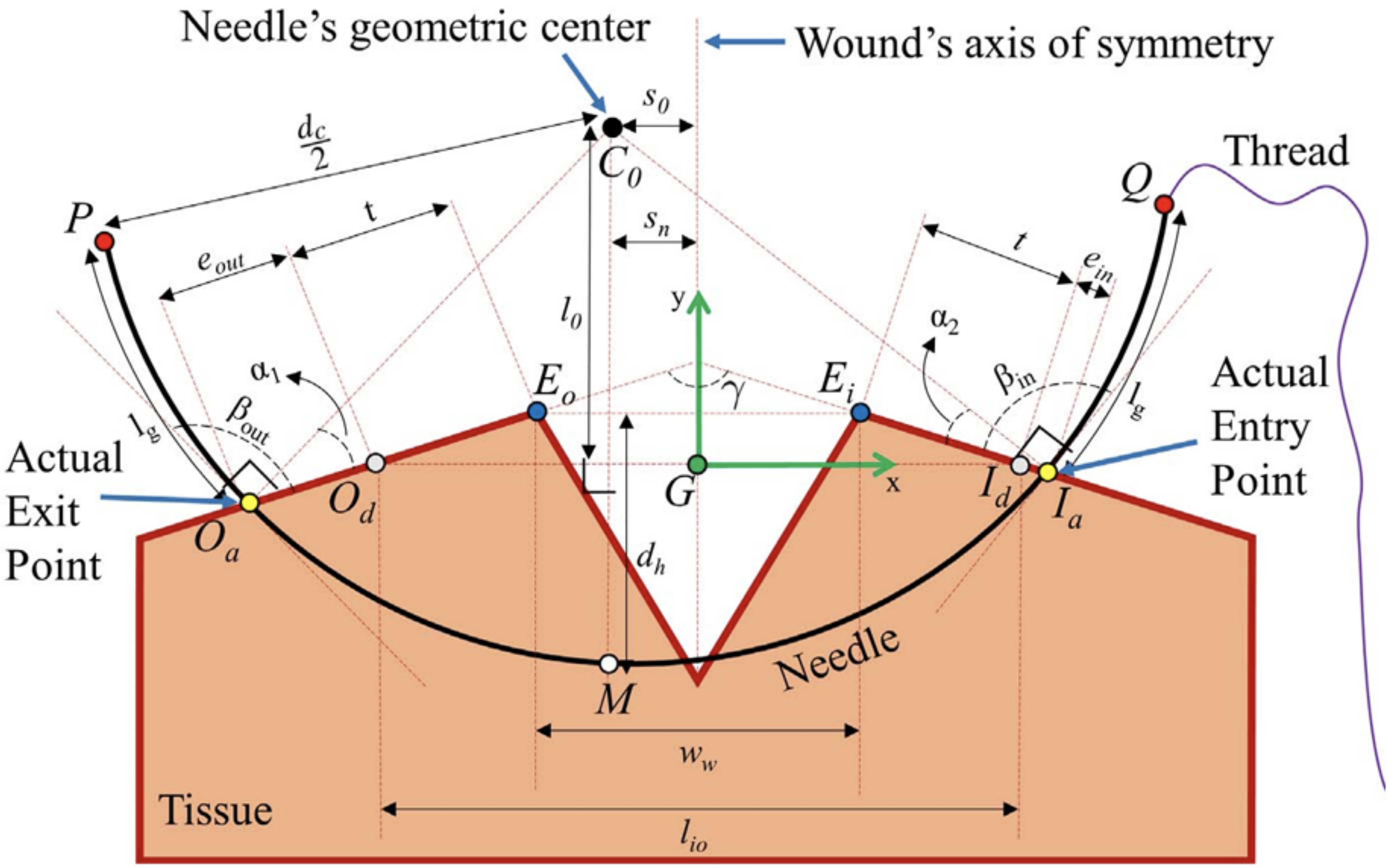




Desired needle trajectory along with entry and exit points[2]

Using sequential convex optimization to get needle path[2]

[2] S. Sen, A. Garg, D. V. Gealy, S. McKinley, Y. Jen, and K. Goldberg, "Automating multi-throw multilateral surgical suturing with a mechanical needle guide and sequential convex optimization," Proceedings - IEEE International Conference on Robotics and Automation, vol. 2016-June, pp. 4178–4185, 2016

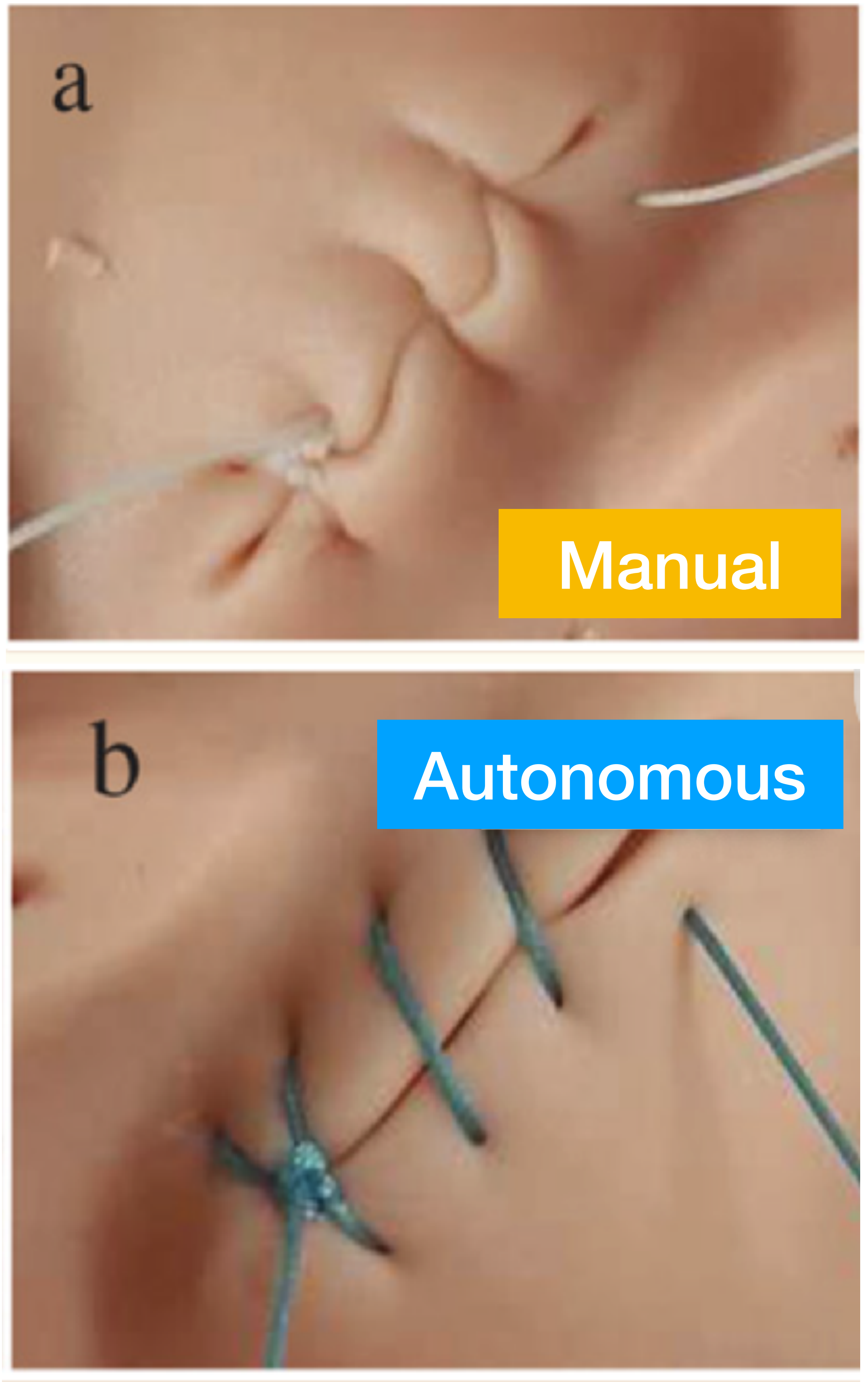


Kinematic model of needle tissue interaction[3]

Pedram et al.[3] present an algorithm for optimal selection of needle diameter, shape and path to minimize tissue trauma

[3] S. A. Pedram, P. Ferguson, J. Ma, E. Dutson, and J. Rosen, “Autonomous suturing via surgical robot: An algorithm for optimal selection of needle diameter, shape, and path,” 2017 IEEE International Conference on Robotics and Automation (ICRA), pp. 2391–2398, 2017.

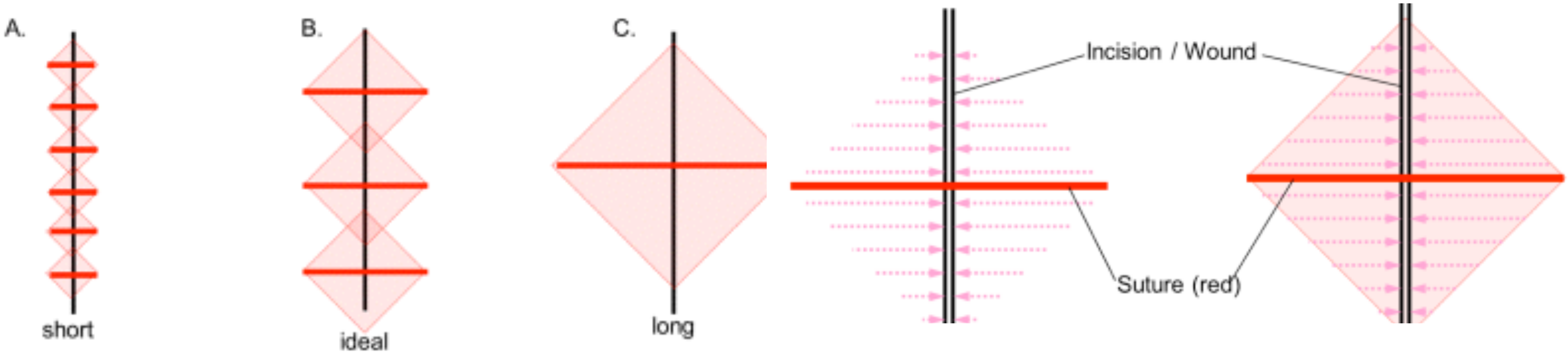
Suture Planning for Linear 2D Wounds



Saeidi et al.[4] developed a suture planning algorithm for linear wounds and implemented suturing with the Smart Tissue Autonomous Robot (STAR) system.

[4] H. Saeidi, H. N. Le, J. D. Opfermann, S. Leonard, A. Kim, M. H. Hsieh, J. U. Kang, and A. Krieger, “Autonomous laparoscopic robotic suturing with a novel actuated suturing tool and 3d endoscope,” Proceedings - IEEE International Conference on Robotics and Automation, vol. 2019-May, pp. 1541–1547, 2019.

Surgeon's "Diamond Rule"

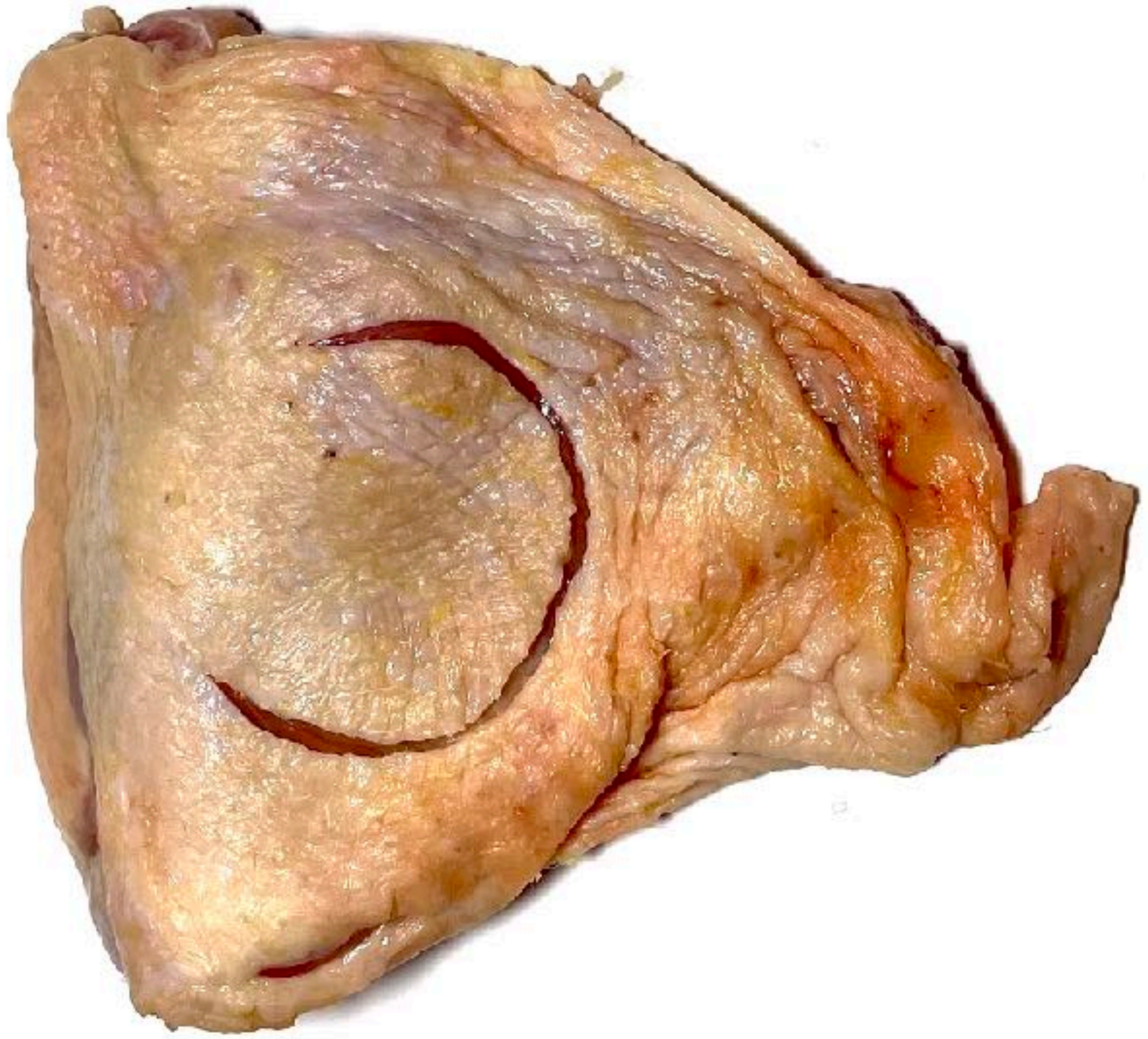


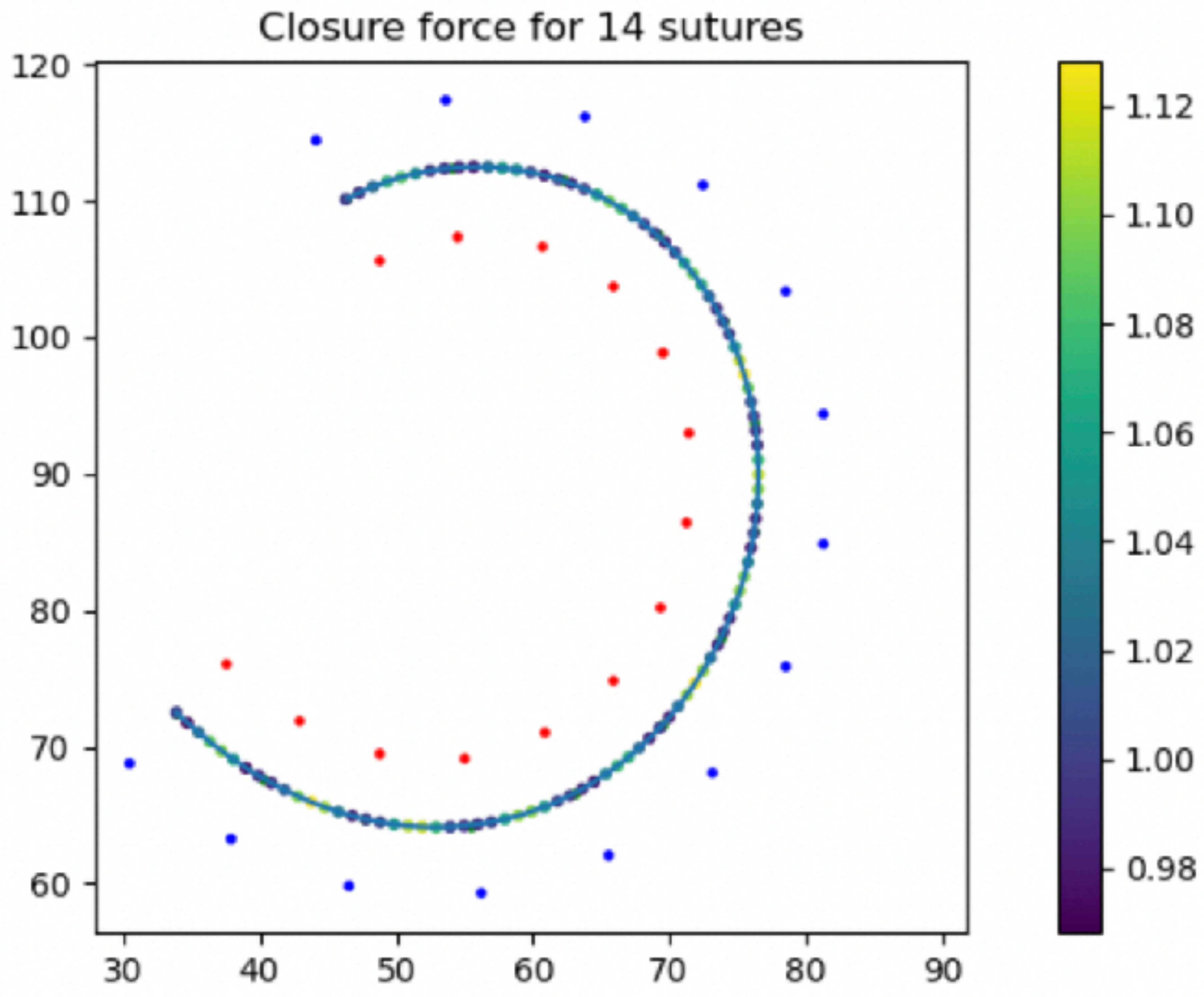
Assumes a linear wound line, and linearly decreasing force along the wound → evenly spaced sutures leads to equal suture forces[5]

[5] Jean Gaston Descoux, Walley J. Temple, Shirley A. Huchcroft, Cyril B. Frank, and Nigel G. Shrive. "Linea Alba Closure: Determination of Ideal Distance Between Sutures". In: Journal of Investigative Surgery 6.2 (1993). PMID: 8512892, pp. 201–209. Doi:10.3109/08941939309141609.

2D **Non-Linear** Suture Planning

Given image of a 2D curved wound and centerline of wound, compute a **suture plan** that meets criteria and minimizes the cost function.



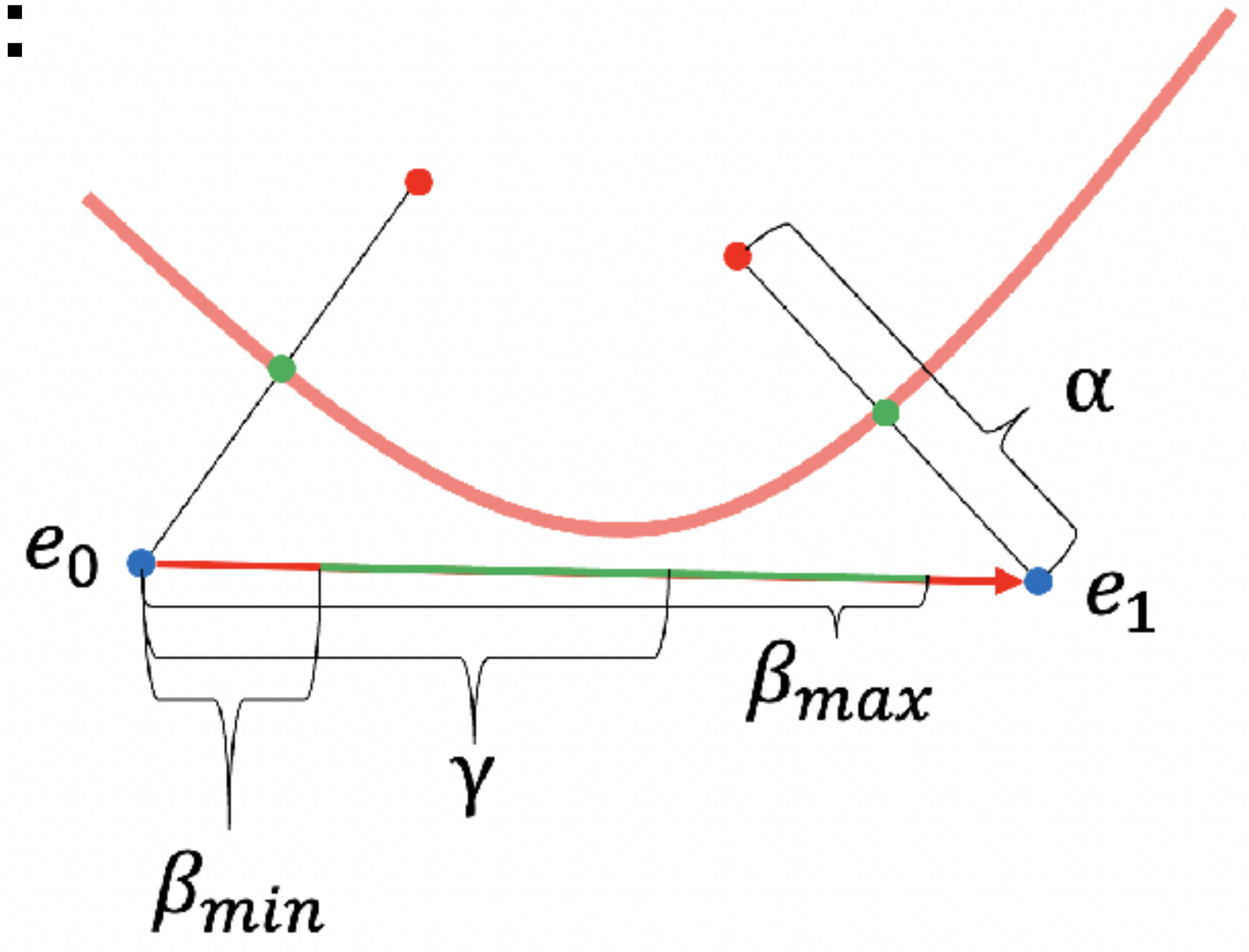


[7] V. Kamat et al., "Automating 2D Suture Placement," 2023 IEEE 19th International Conference on Automation Science and Engineering **(CASE),** Auckland, New Zealand, **2023**, pp. 1-8, doi: 10.1109/CASE56687.2023.10260435.

4-Part Cost Function

Cost due to Deviations from Ideal Suture Distance:

$$L^{\mathrm{idl}}(s_1,\ldots,s_n) = \sum_{z(\cdot)} \frac{1}{n+1} \sum_{i=0}^{n} \left(\|z(s_{i+1}) - z(s_i)\| - \gamma \right)^2$$

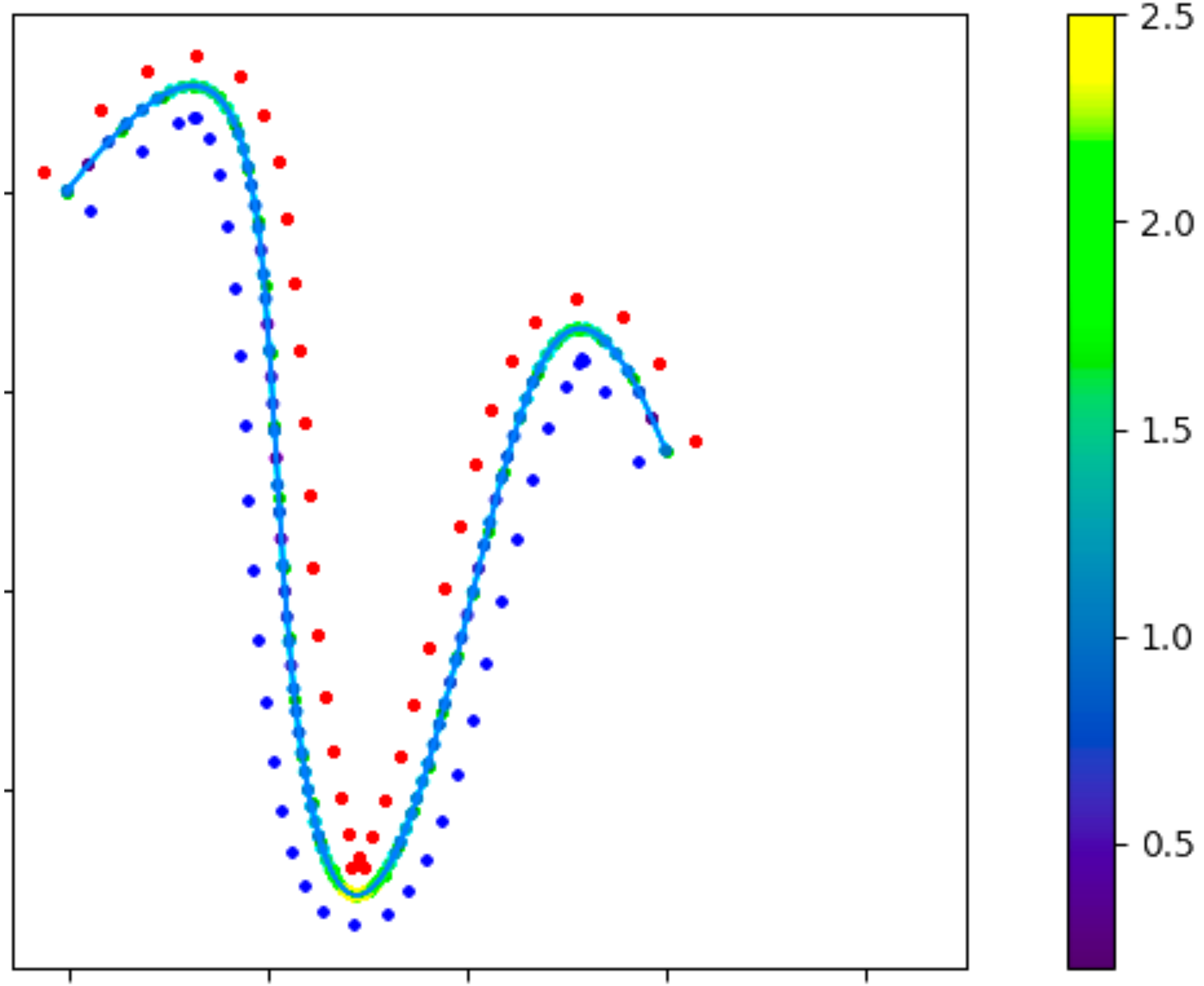


Cost due to Variance of Suture Distances:

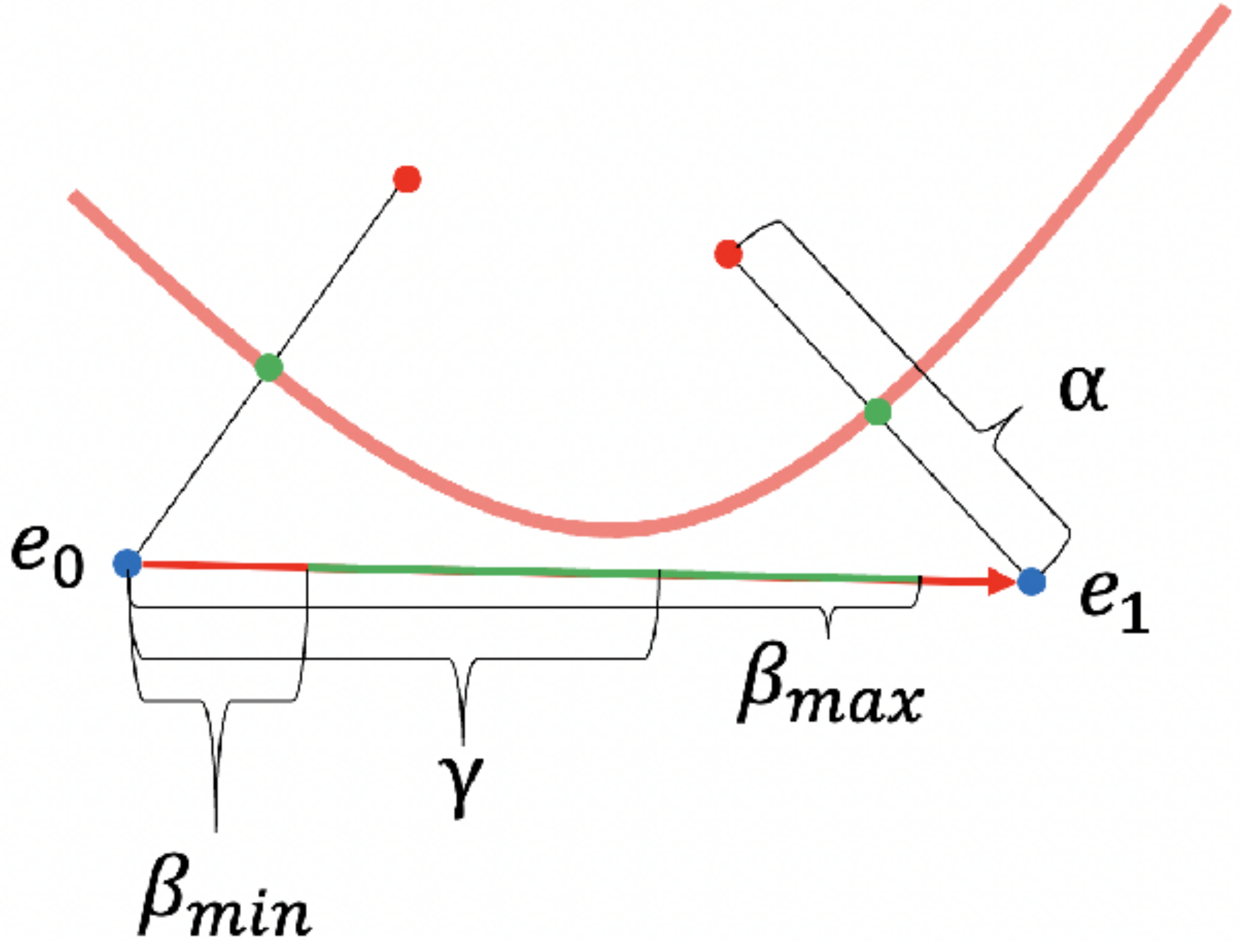
$$L^{\mathrm{var}}(s_1,\ldots,s_n) = \sum_{z(\cdot)} \mathrm{Var}\left(\{\|z(s_{i+1}) - z(s_i)\|\}_{i=0}^{n} \right)$$

Skin Tension

Blue = Low
Yellow = High

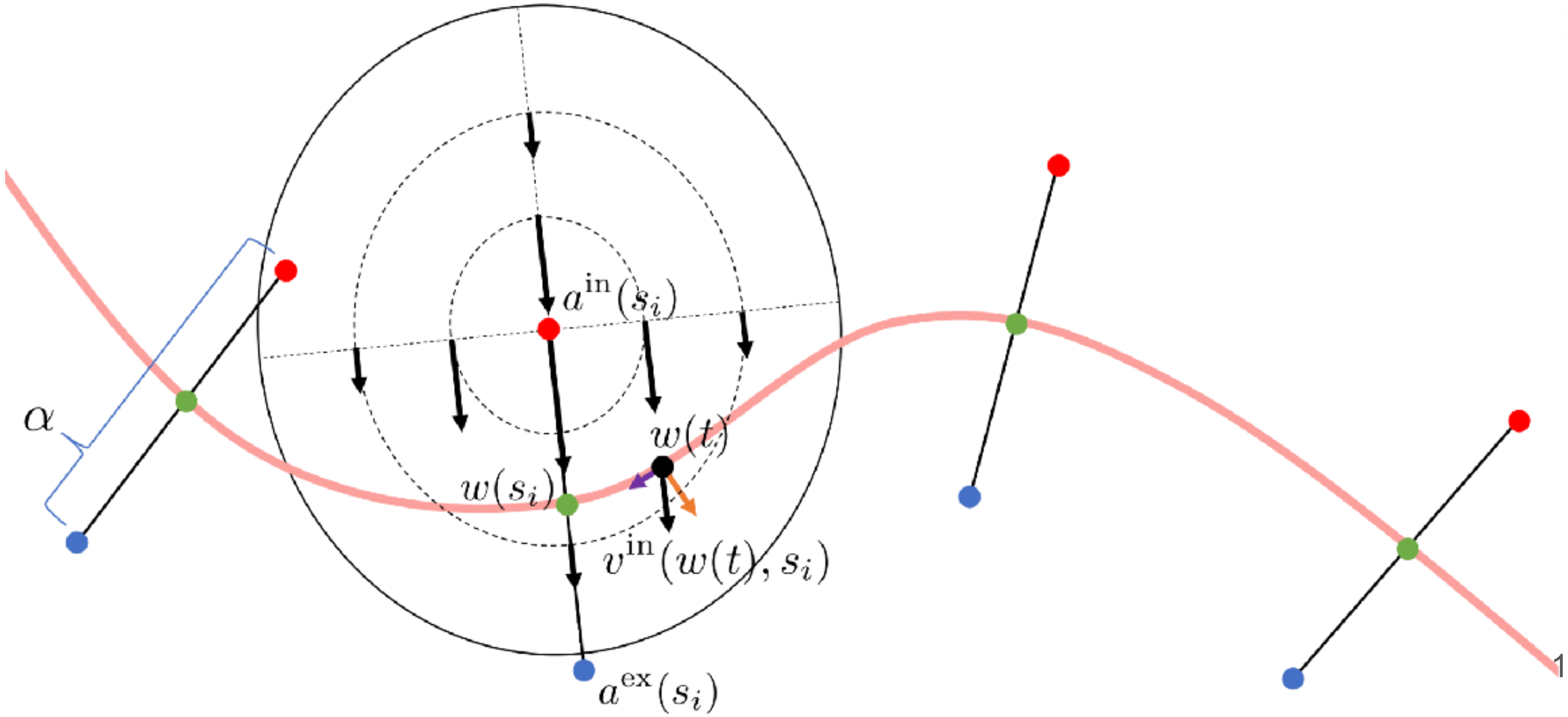


Cost Function (cont'd)



Cost due to Deviations from Ideal Closure Force:

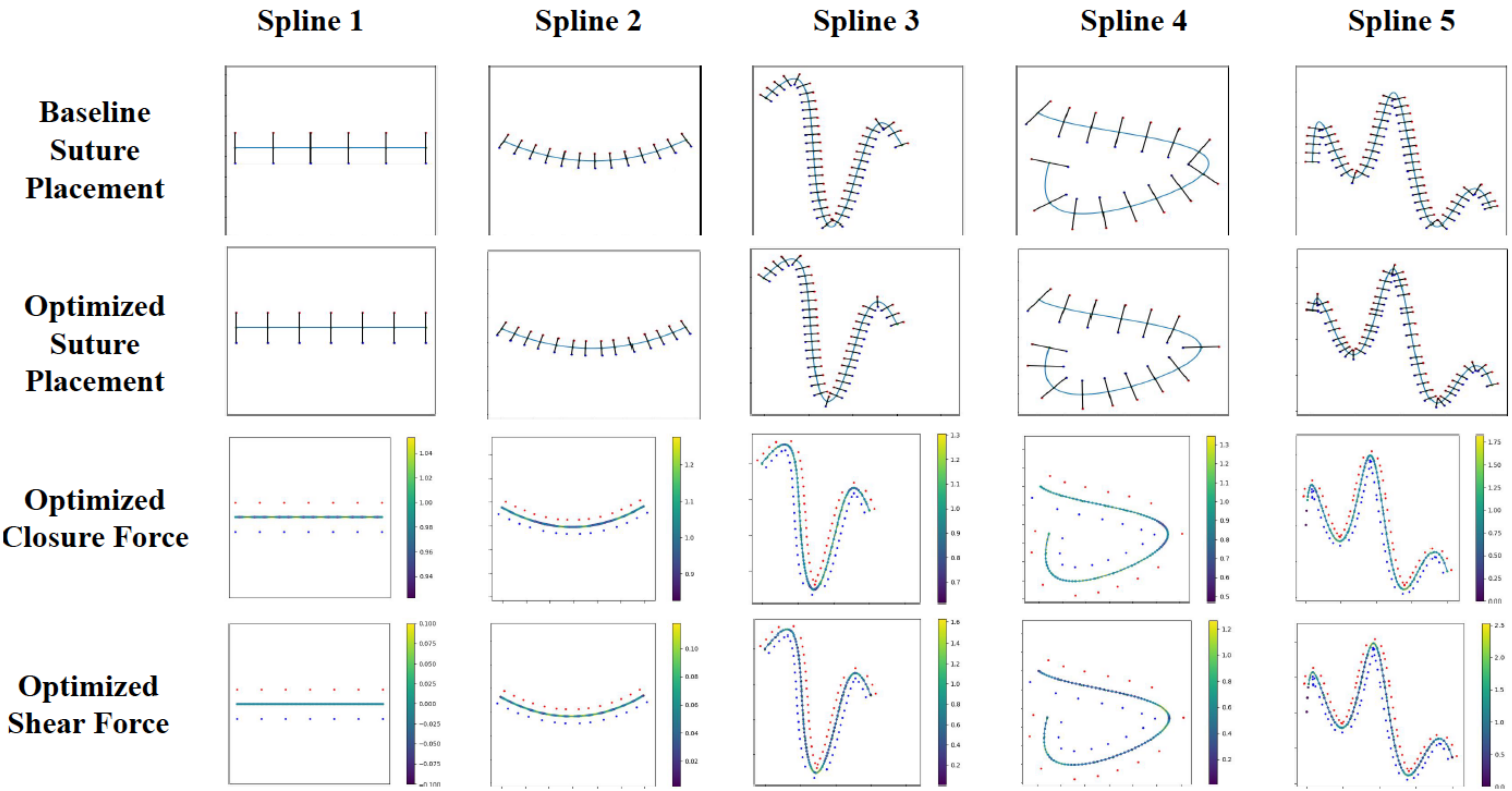
$$L_{\mathrm{c}} = \frac{1}{m} \sum_{j=1}^{m} (1 - f^{\mathrm{c}}(t_j))^2$$



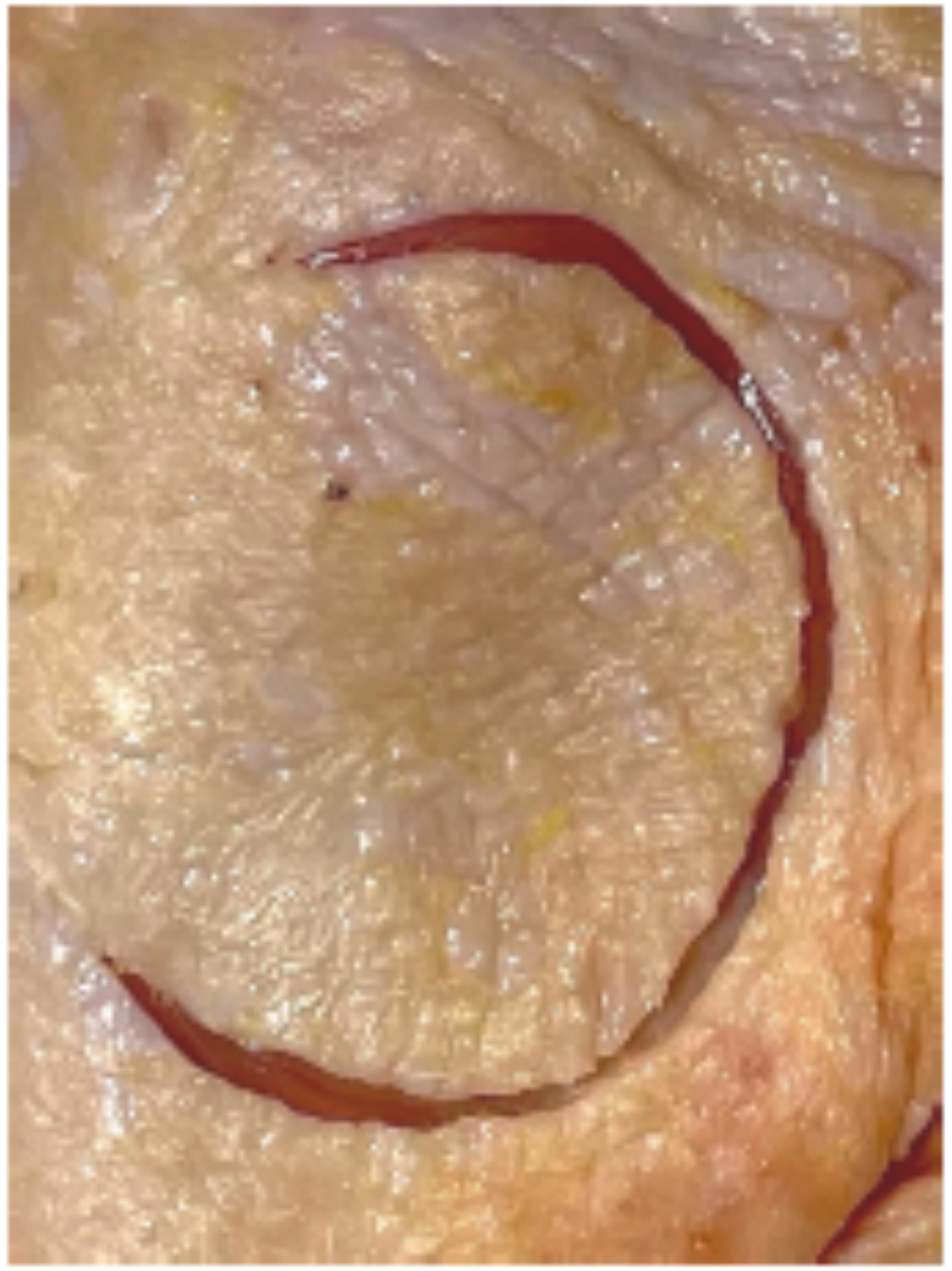
Cost due to Shear Force:

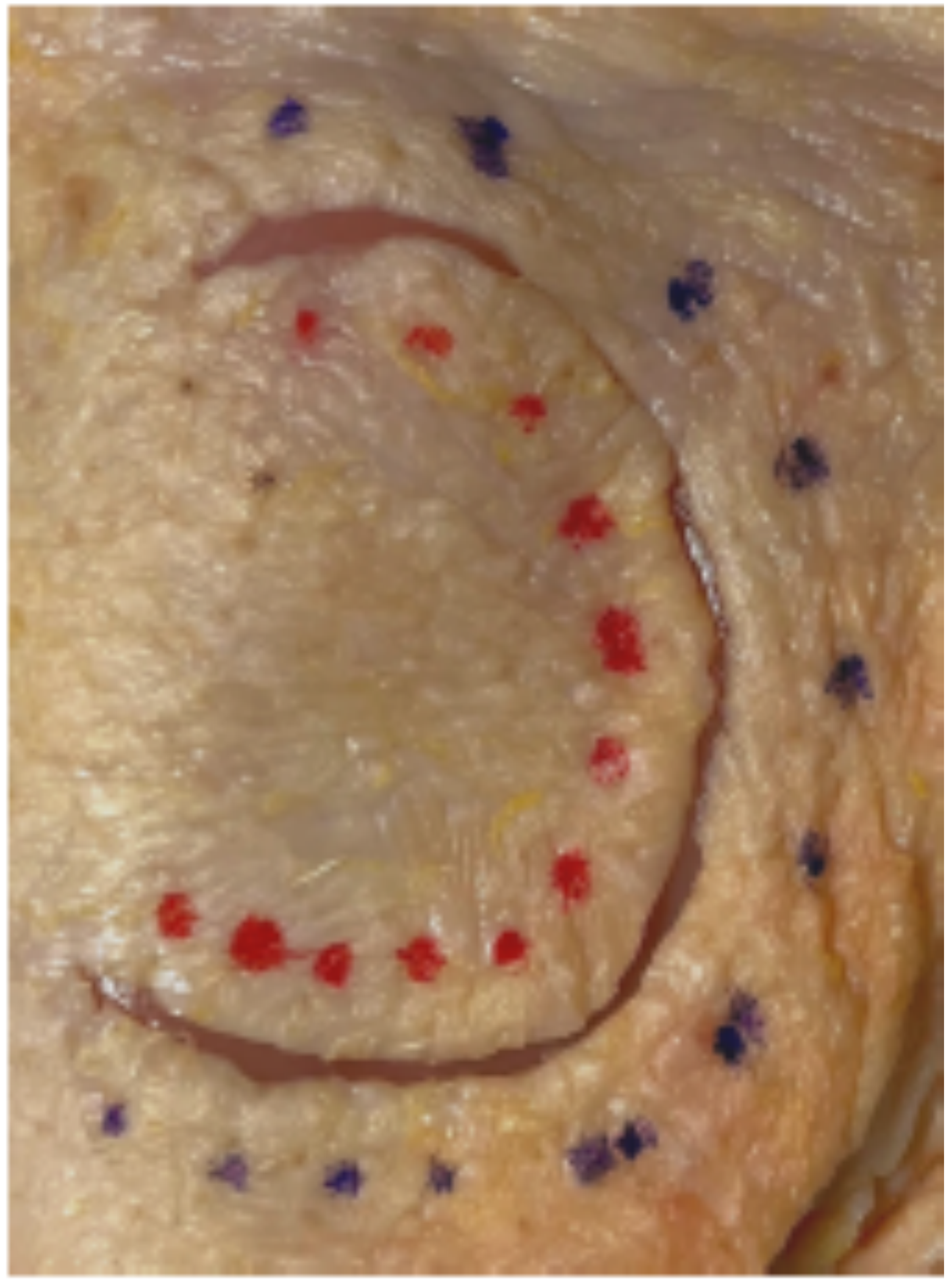
$$L_{\mathrm{s}} = \frac{1}{m} \sum_{j=1}^{m} f^{\mathrm{s}}(t_j)^2$$

2D Simulation Experiments

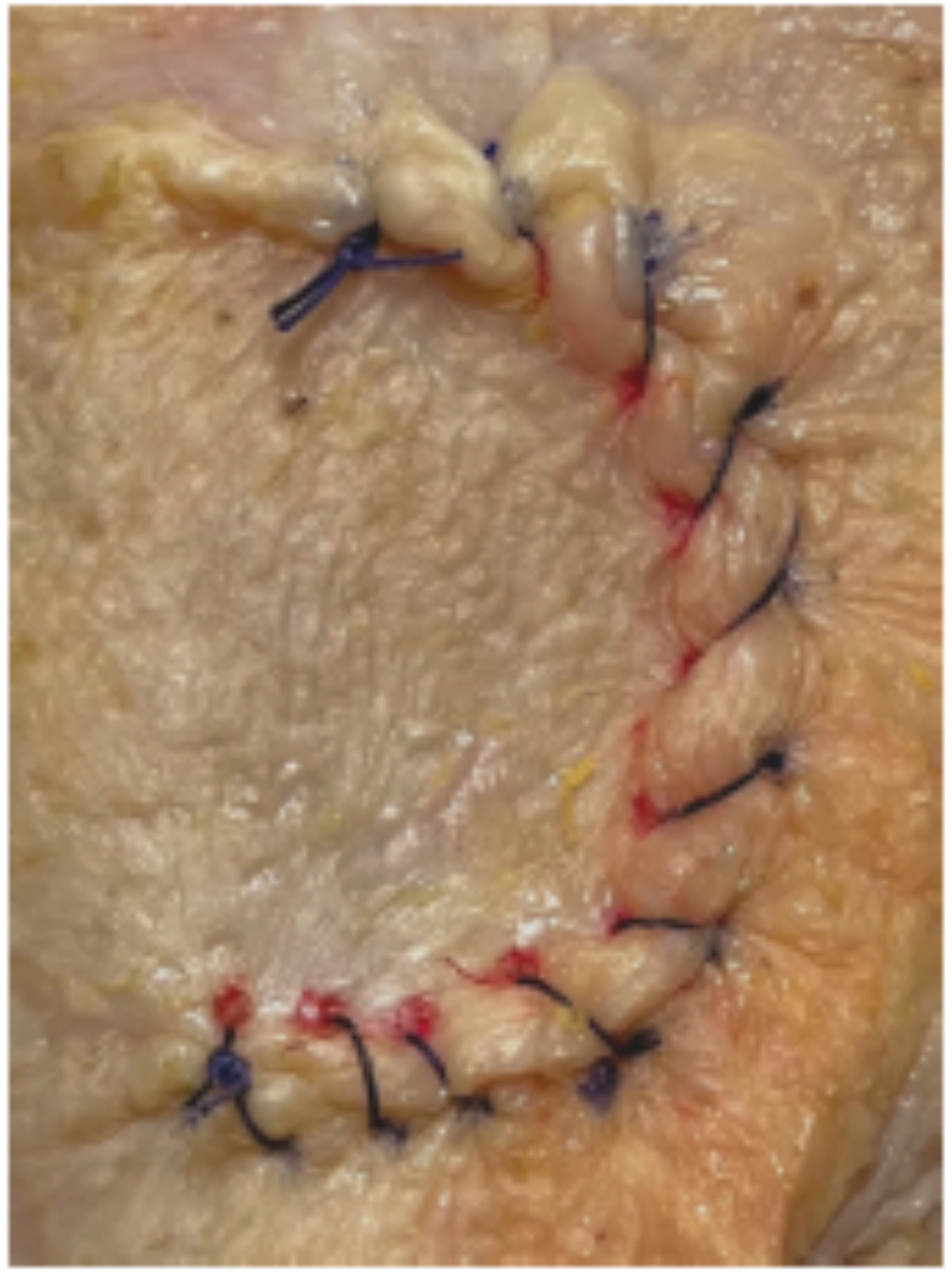


2D Physical Experiment: Chicken Skin





SP2DEEF

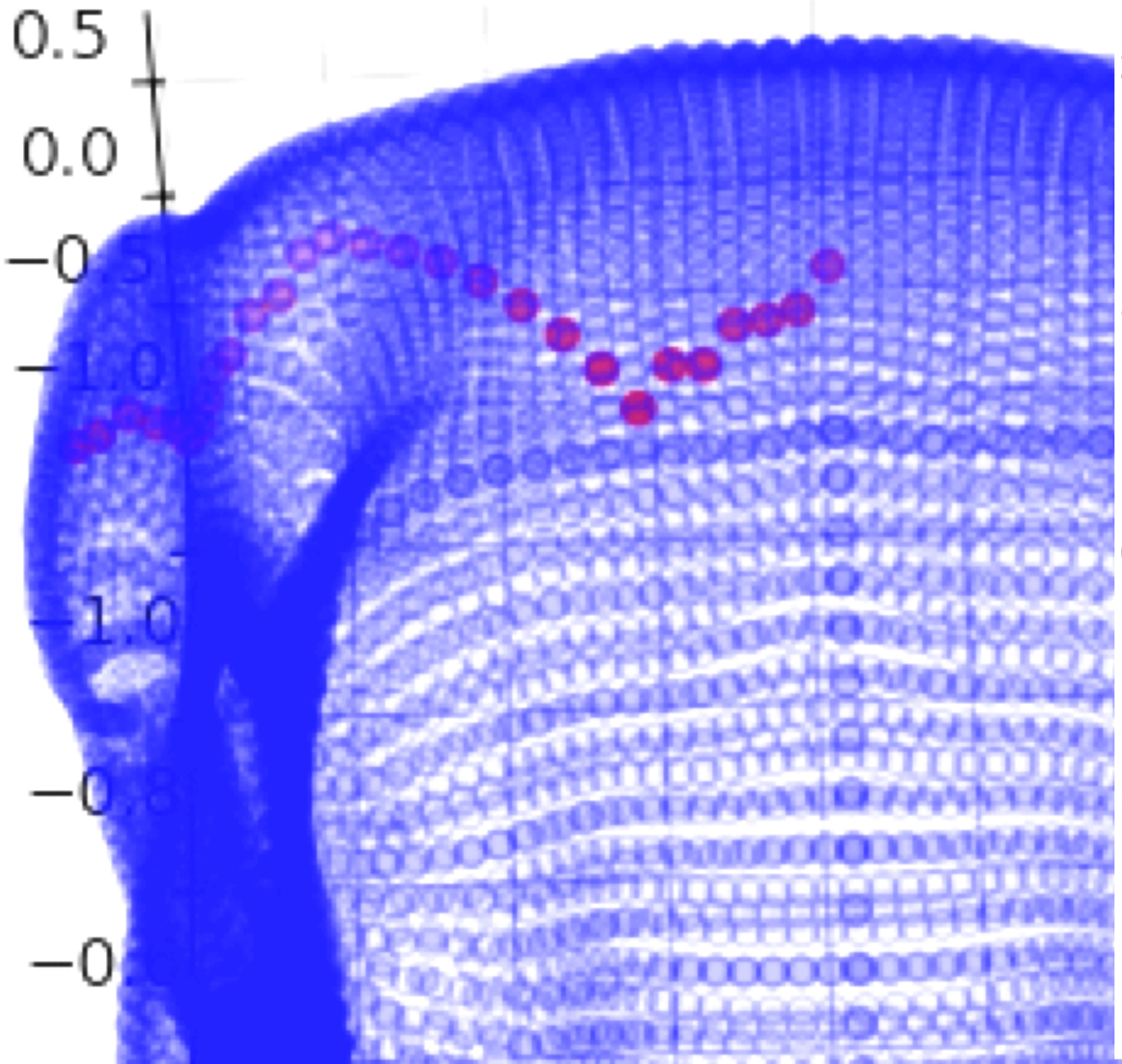


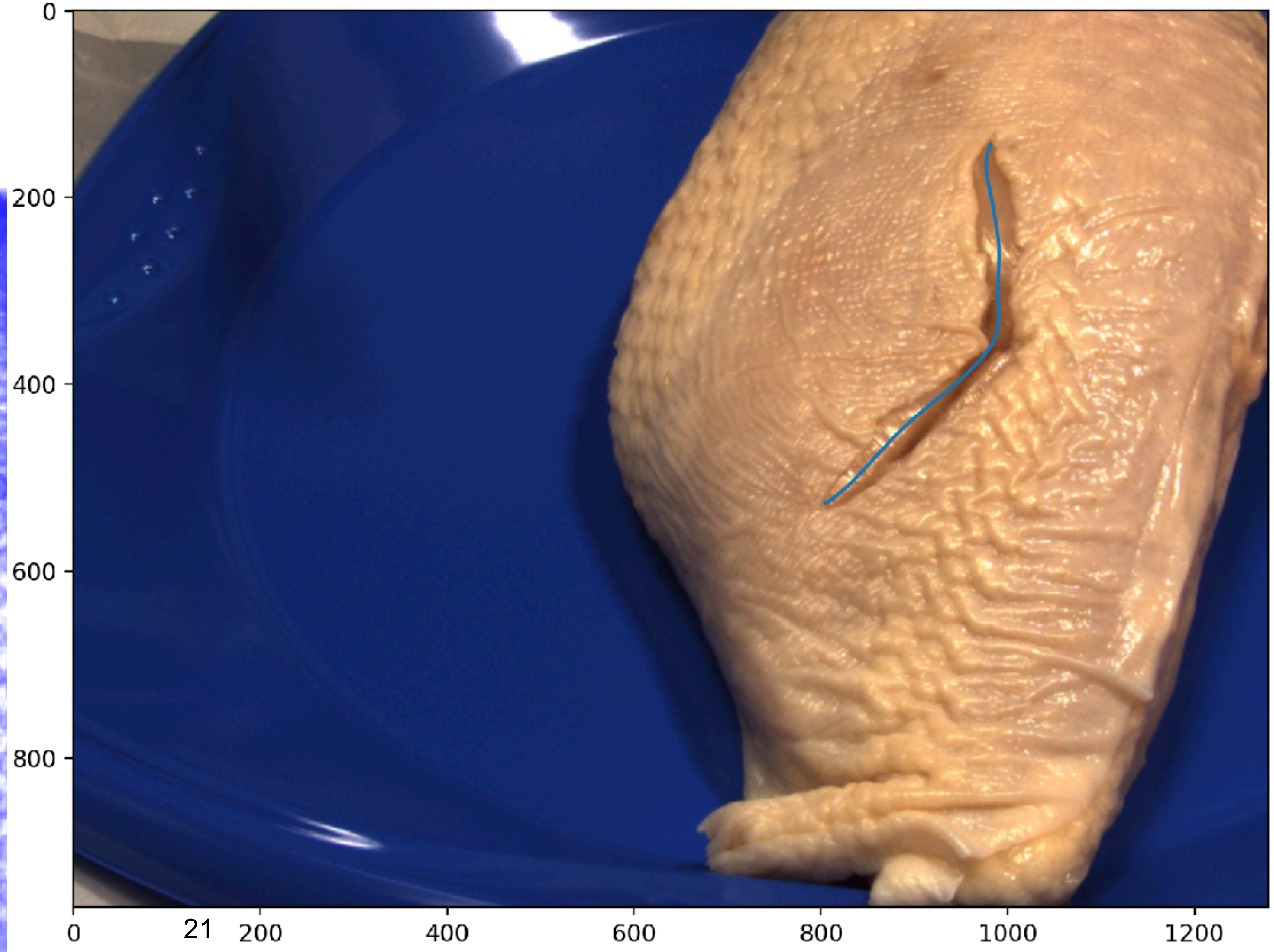
SP2DEEF

Surgeon

This Paper: **3D** Non-Linear Suture Planning

Wound is curved across a 3D manifold





SP3DEEF:

Suture

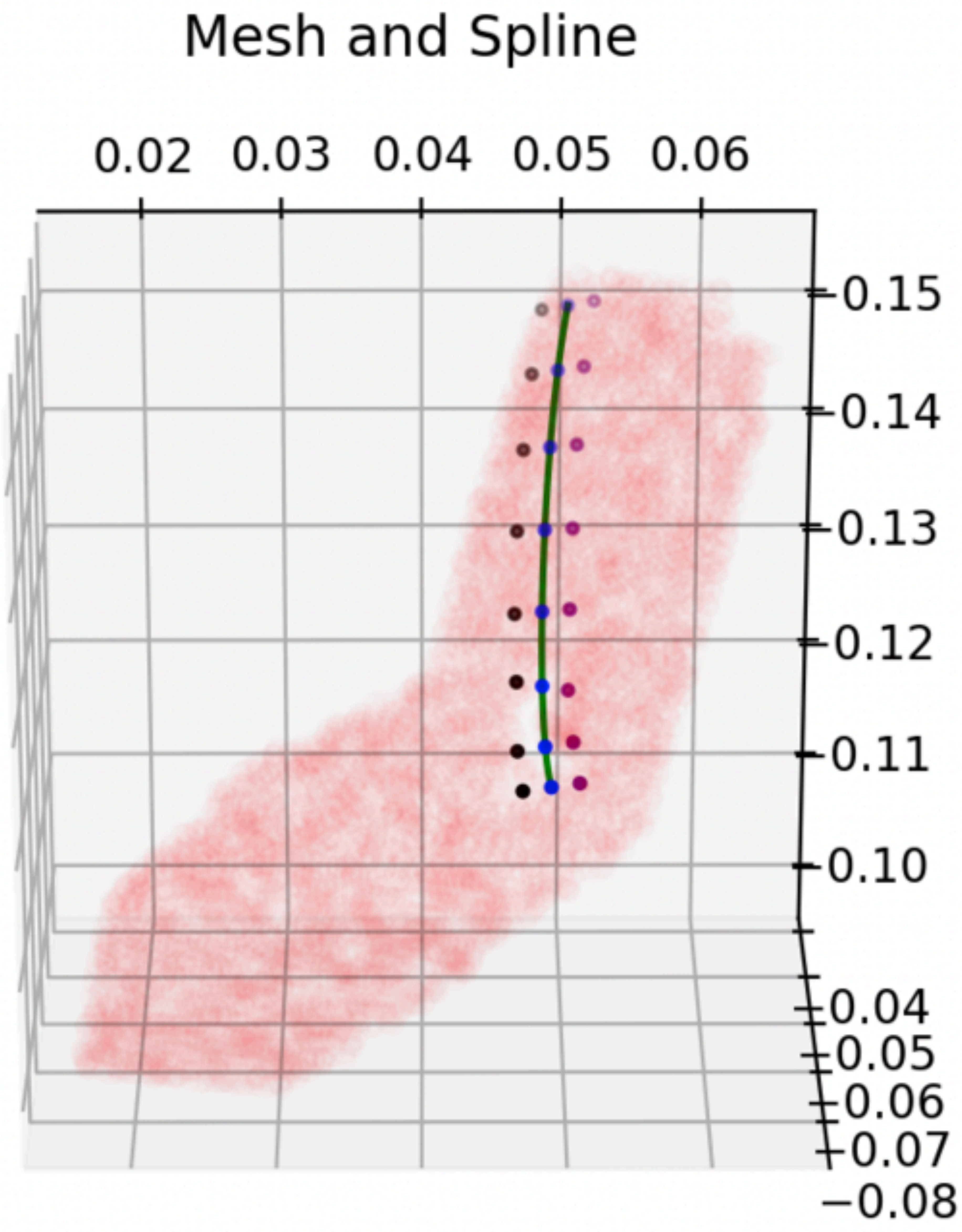
Planning in

3D

Equalizing

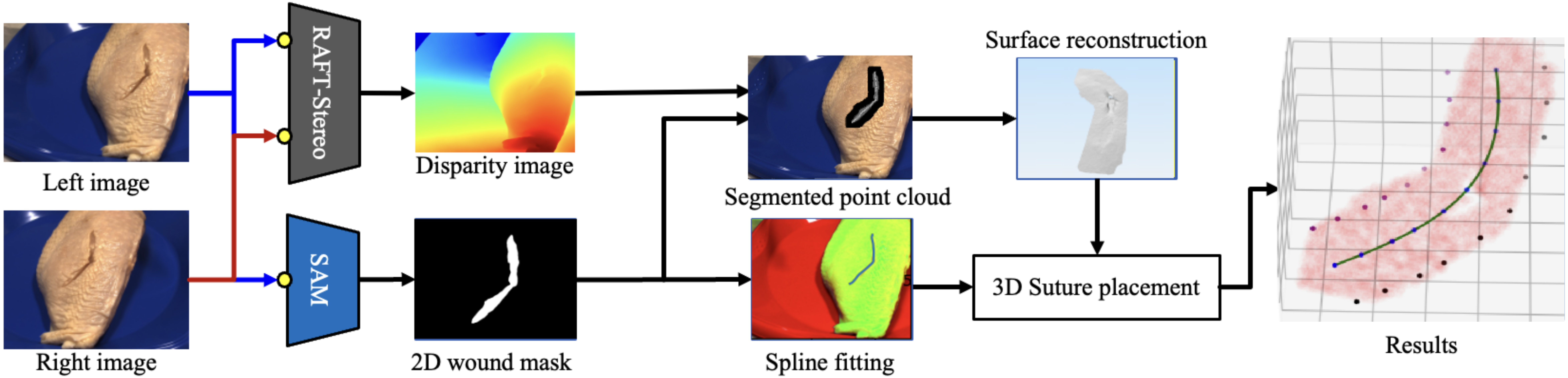
Elliptical

Forces

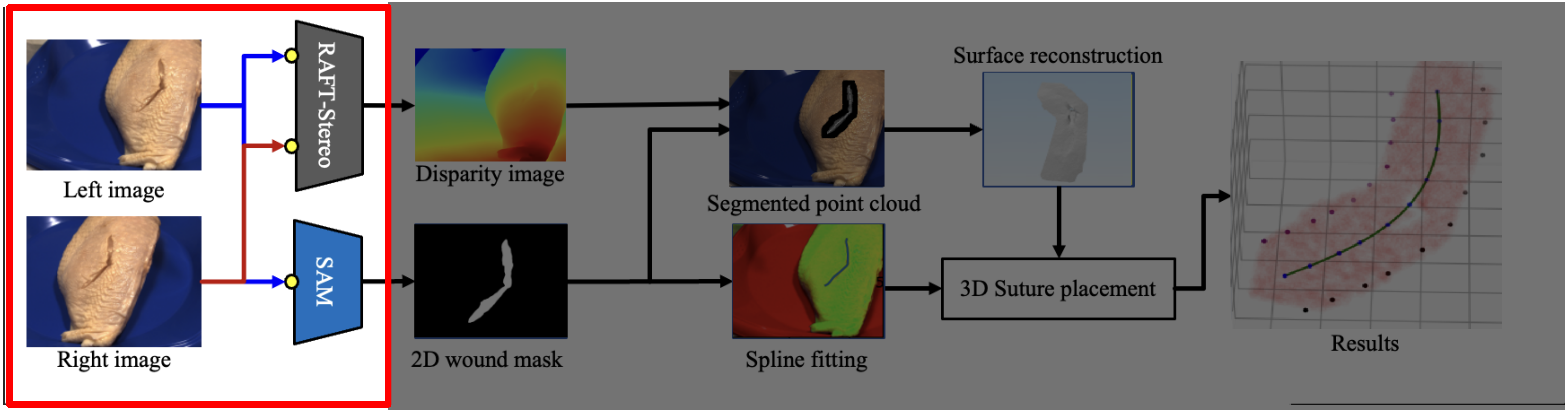


3D Suture Planning Problem

Given **2 stereo images** of a wound without branches and a bounding box around the wound, produce a **suture plan** that meets criteria and minimizes the cost function.



Step 1: 3D Image Processing



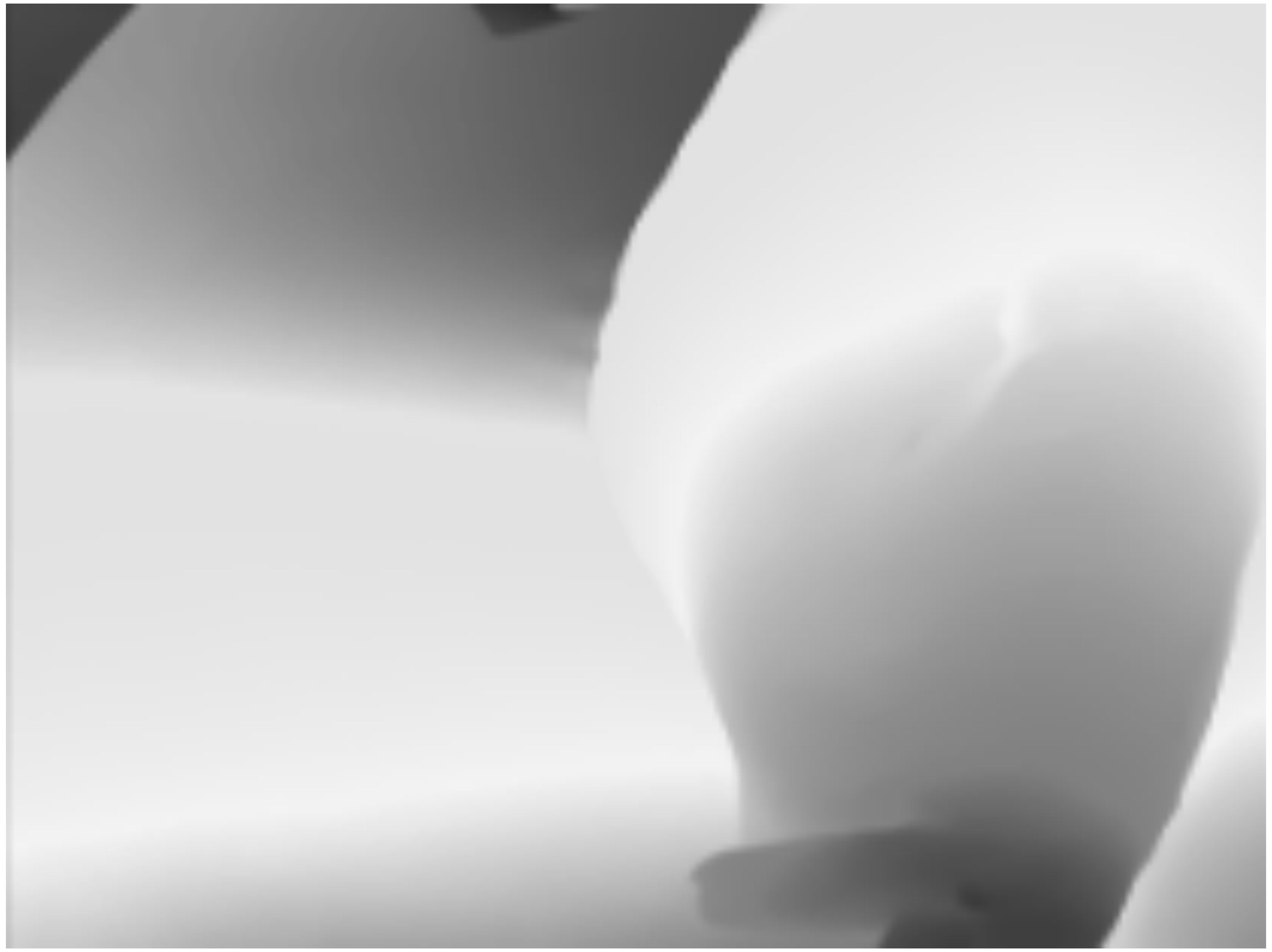
Step 1: 3D Image Processing

Left image

Right image

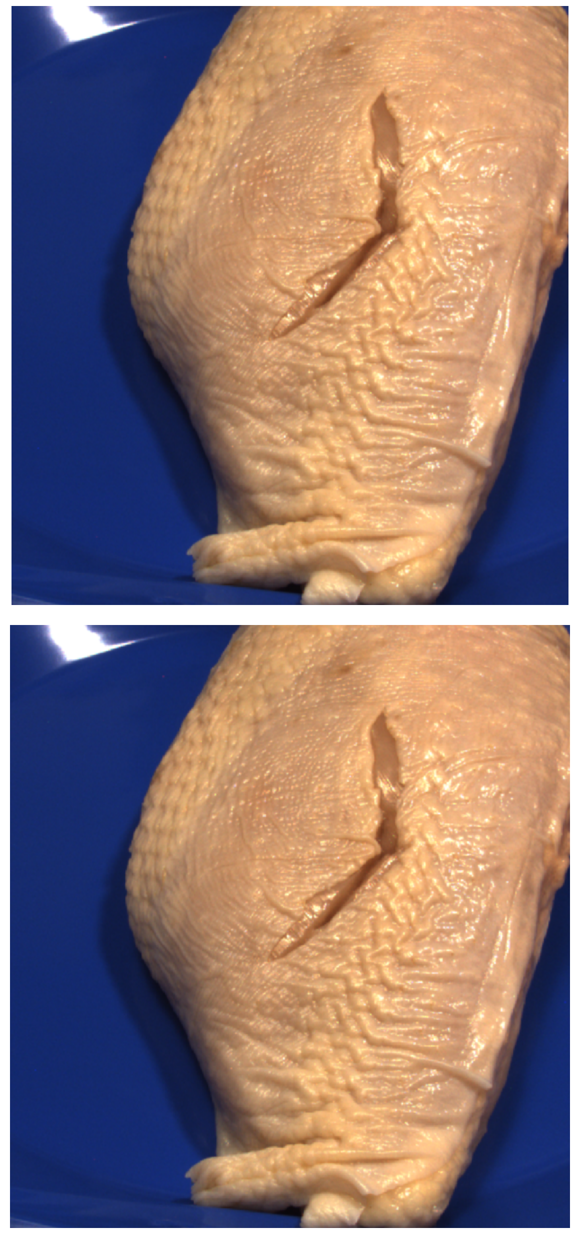
Step 1: 3D Surface Estimation

Wound Mask (from both cameras)

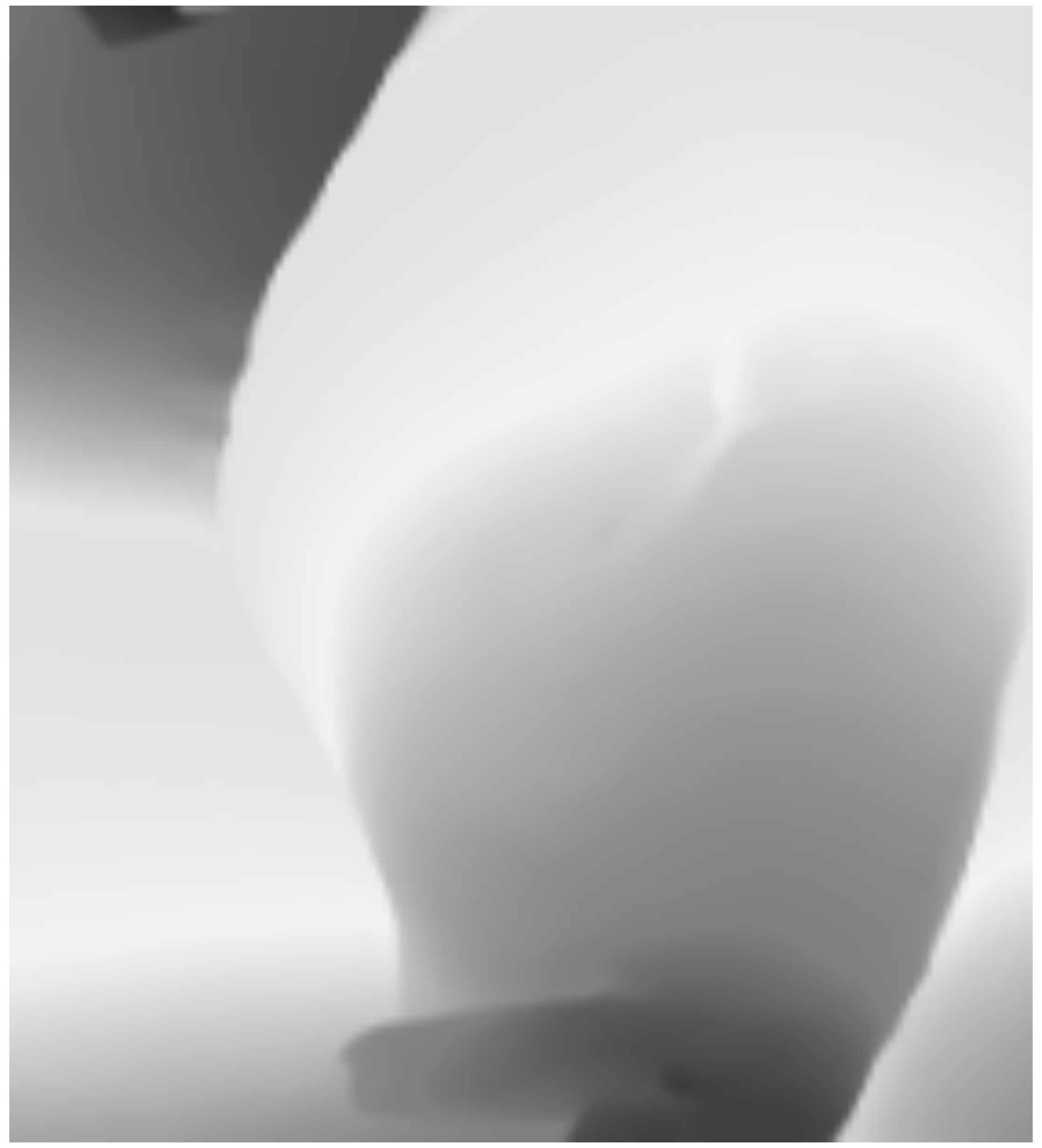


Disparity Image (amount of parallax, proxy for depth)

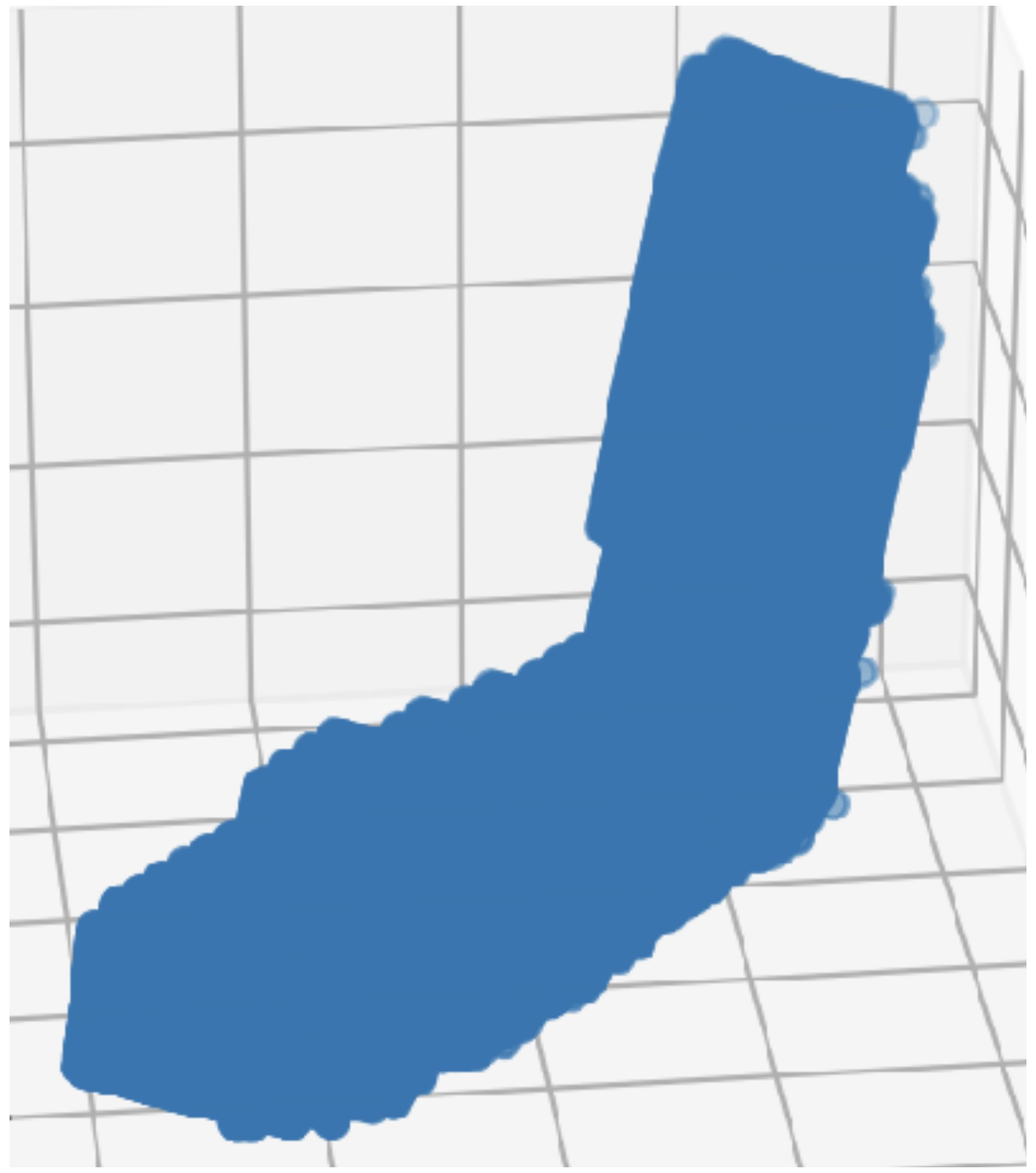
Step 1: 3D Surface Estimation



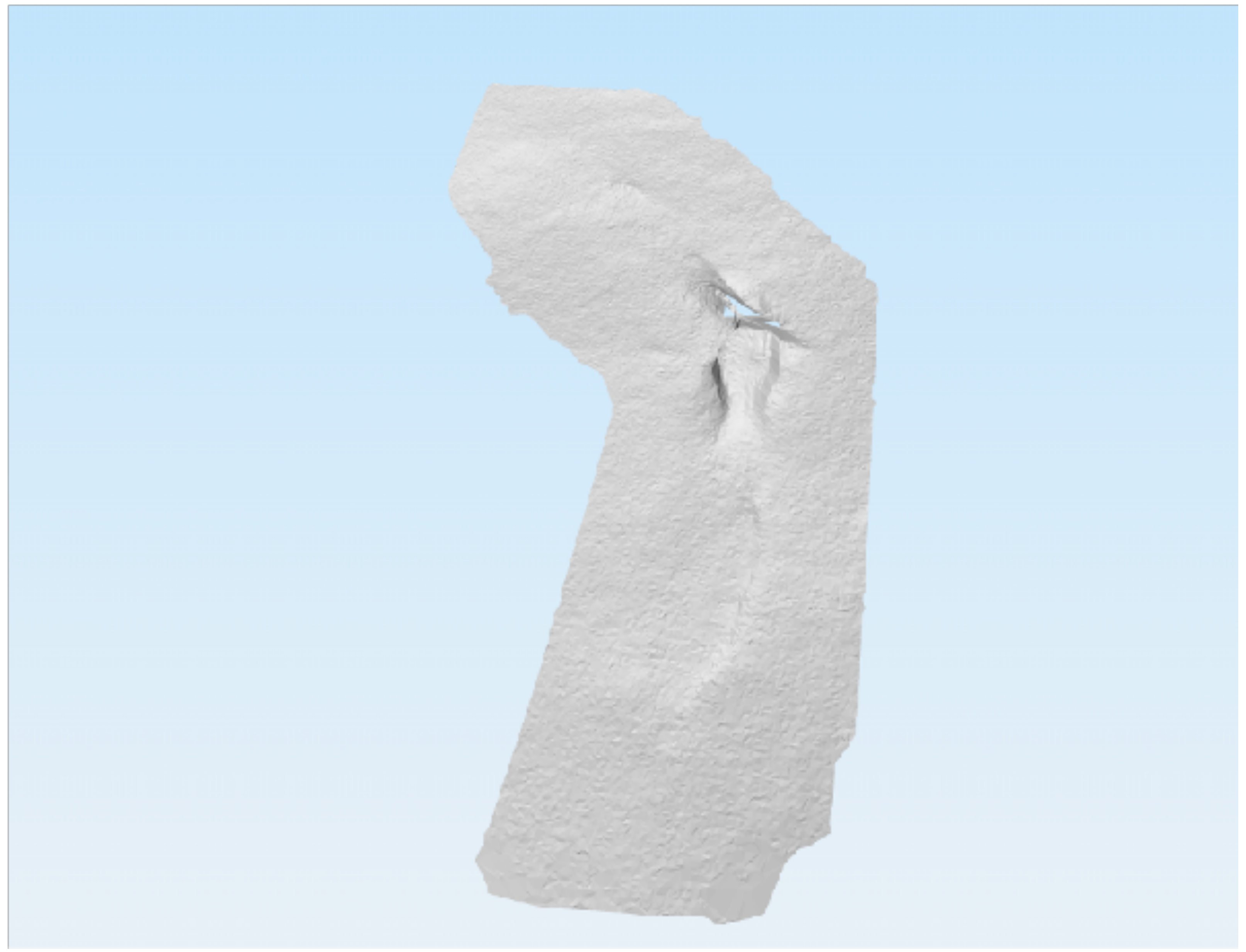
Stereo Pair Images



Disparity Image



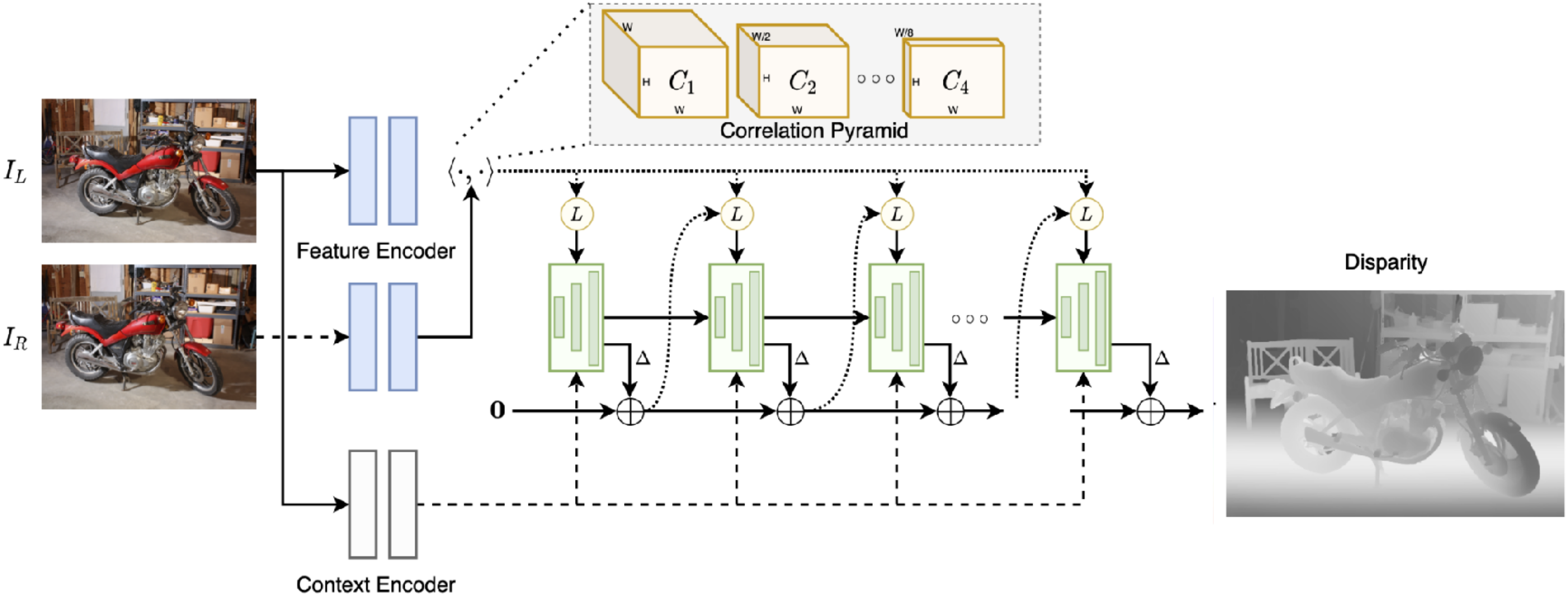
3D points



Surface, generated from points by advancing point algorithm

[10] Da TKF, Cohen-Steiner D. Advancing front surface reconstruction. CGAL User and Reference Manual; CGAL, 2024. https://doc.cgal.org/latest/Advancing_front_surface_reconstruction/index.html.

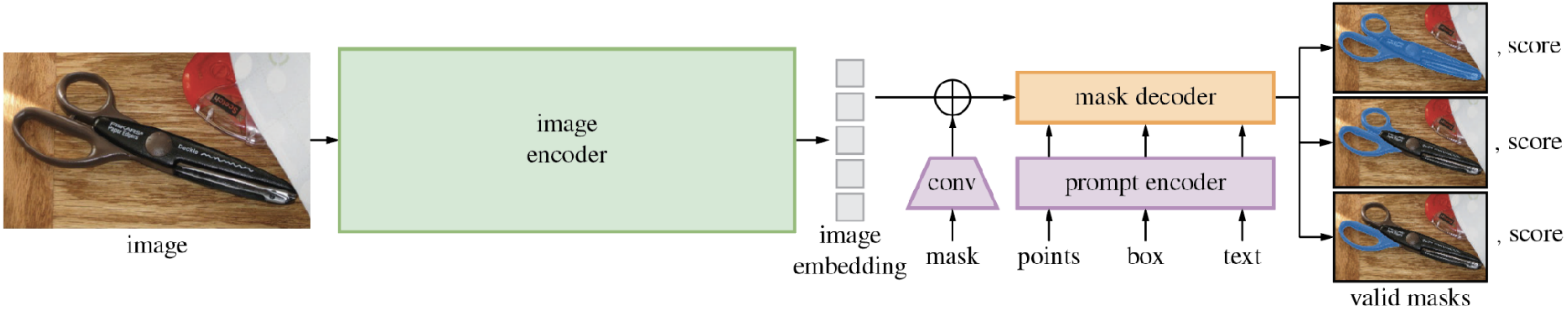
Step 1: RAFT-Stereo: Deep Learning



[8] L. Lipson, Z. Teed and J. Deng, "RAFT-Stereo: Multilevel Recurrent Field Transforms for Stereo Matching," *2021 International Conference on 3D Vision (3DV)*, London, United Kingdom, 2021, pp. 218-227, doi: 10.1109/3DV53792.2021.00032.

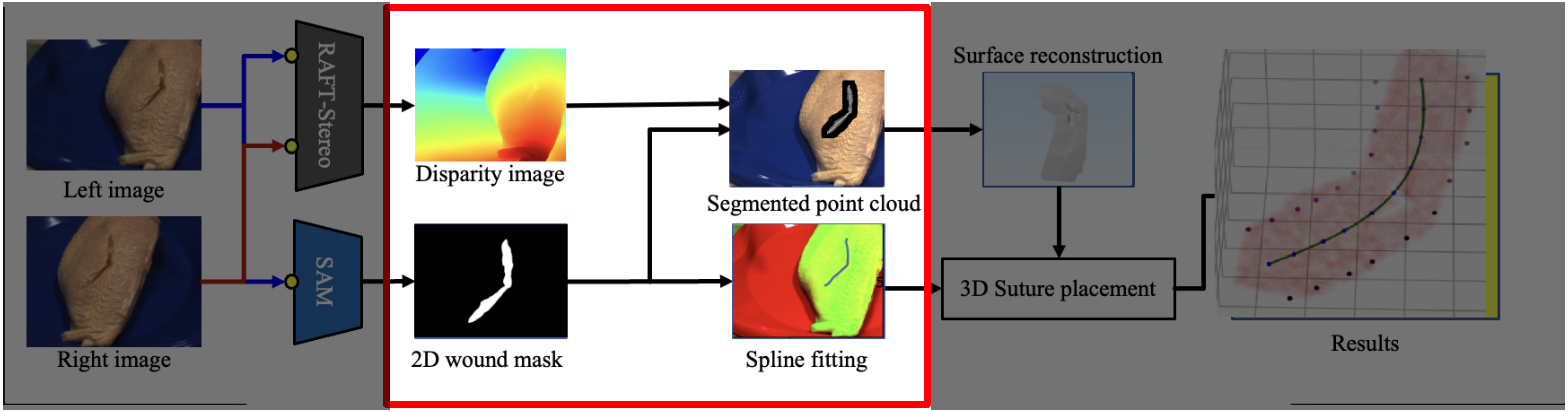
Step 2: Compute Wound Line

Step 2: Meta Segment Anything (SAM)
First application to surgical wound segmentation



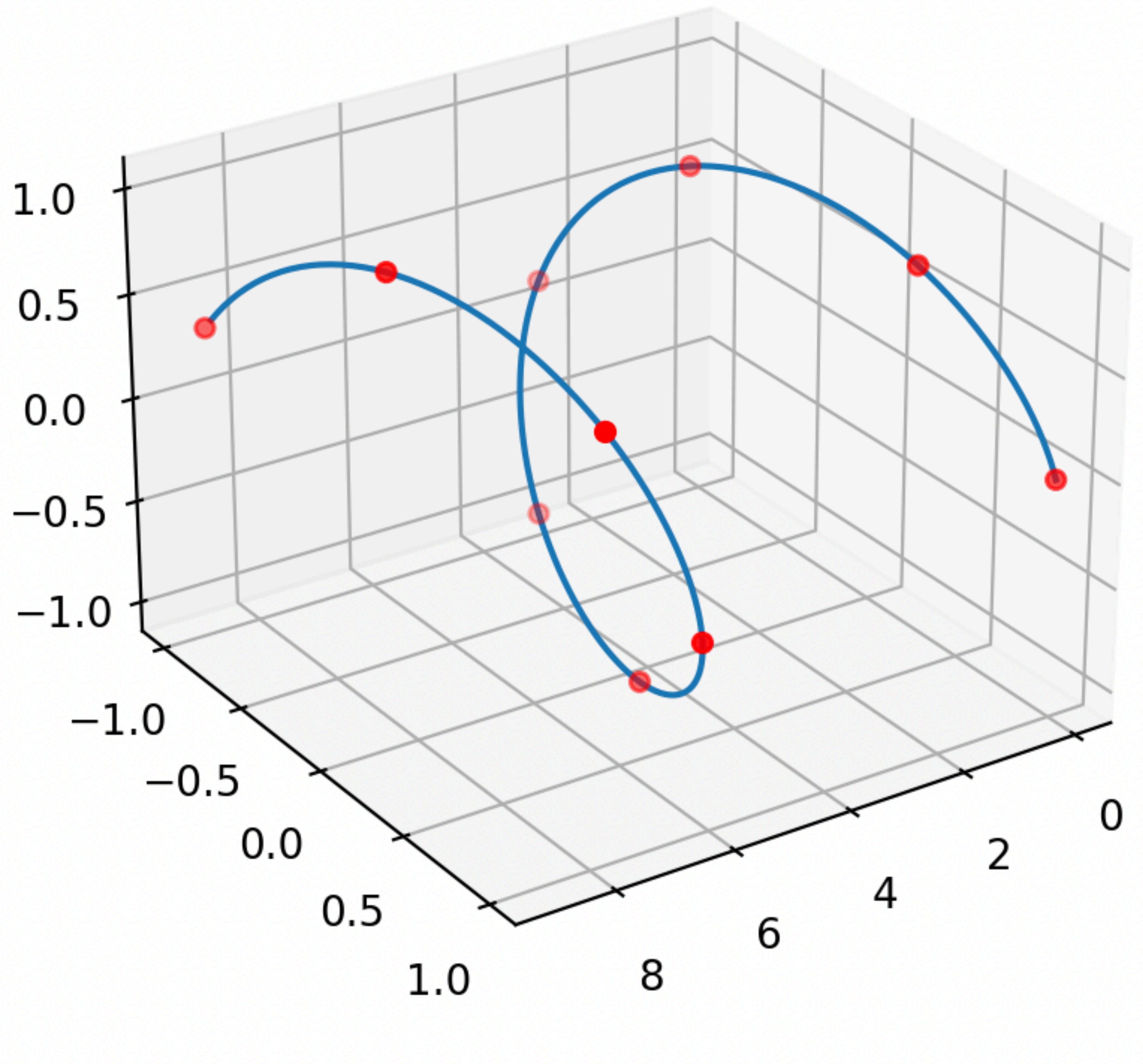
[9] A. Kirillov *et al.*, "Segment Anything," *IEEE/CVF International Conference on Computer Vision (ICCV)*, Paris, France, 2023

Step 3: Fit 3D Spline to Wound Line

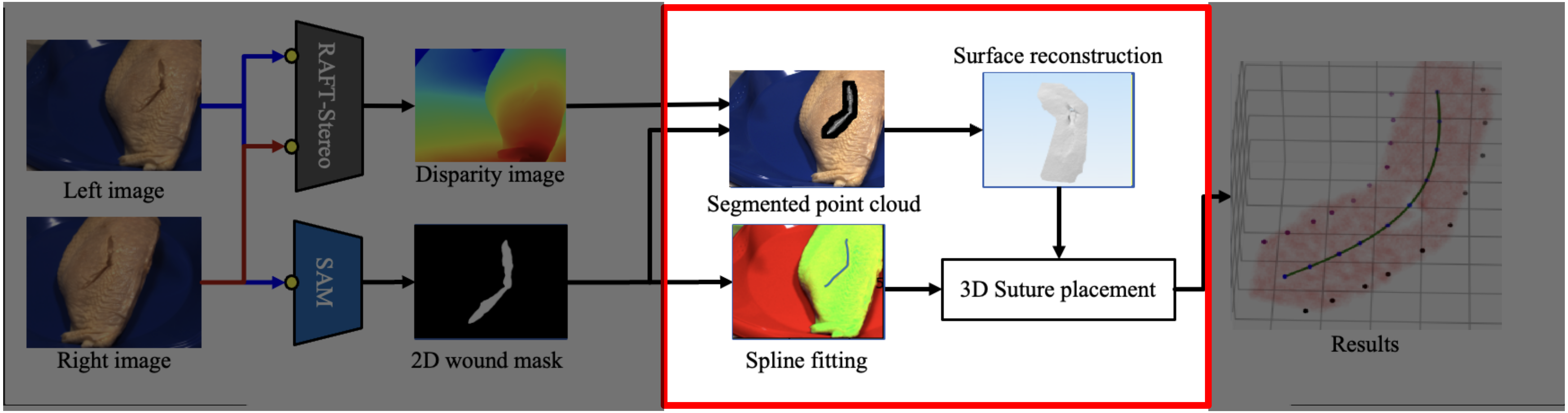


Step 3: 3D Cubic Spline

- Cubic spline in 3D with "knot points"
- Number of knots varies with the length of the line
- Single-pixel wide wound line → Transform to 3D using RAFT
  - Each transformed pixel is used as a knot in 3D spline



Step 4: Optimize 3D Suture Points



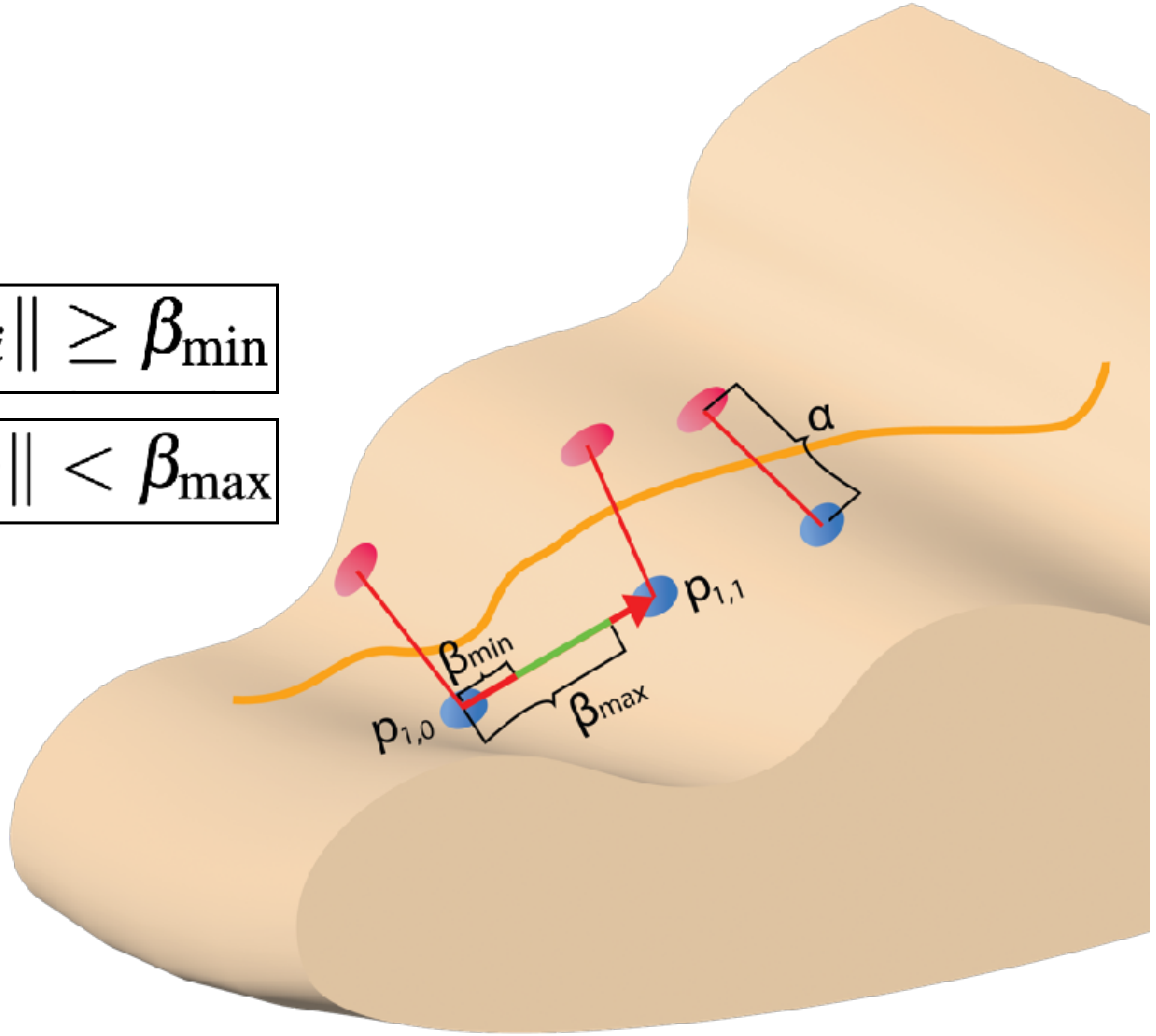
Step 4: 3D Distance Constrains

Insertion/Extraction points must not be:

- too close together
- too far apart

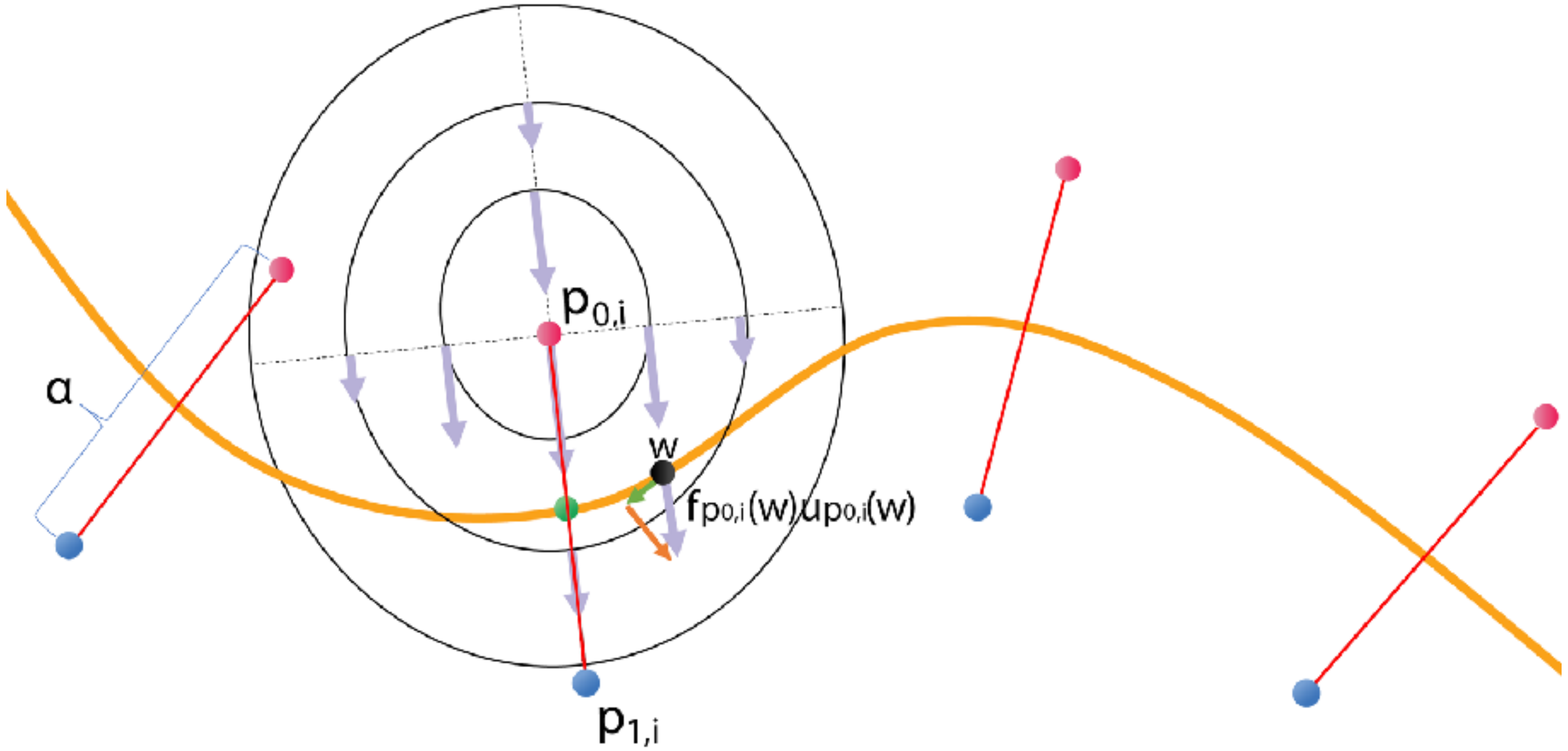
$$\boxed{\|p_{0,i} - p_{1,i}\| \geq \beta_{\text{min}}}$$

$$\boxed{\|p_{0,i} - p_{1,i}\| < \beta_{\text{max}}}$$



Step 4: 3D Cost Functions

- Squared Error from ideal suture width (gamma)
- Variance in distances between successive sutures (for center/insertion/extraction)
- Shear Force
- Difference in Closure force from ideal



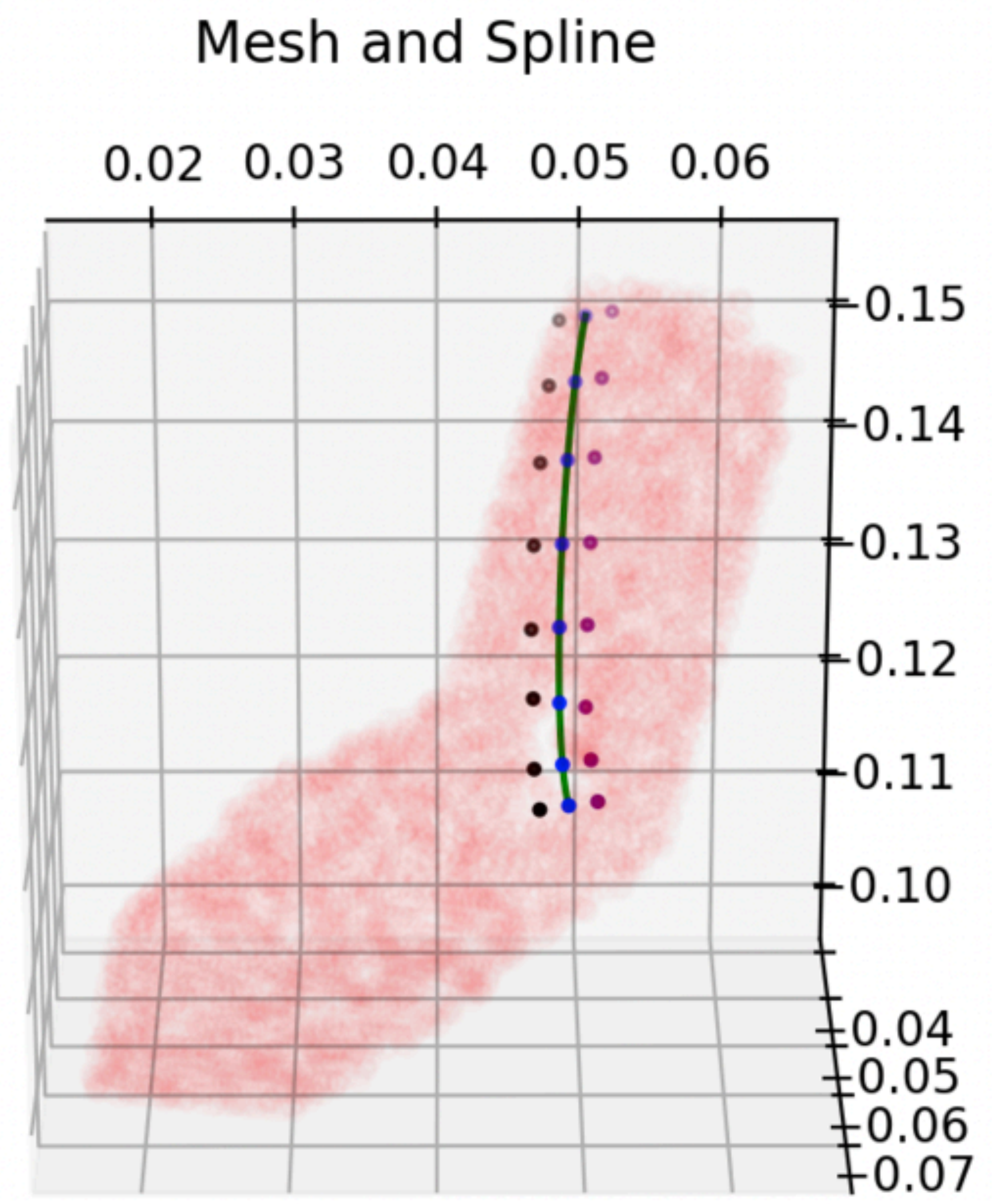
$$\min_{\{s_0,\ldots,s_{n-1}\}} \quad c_d L_d + c_i L_i + c_w L_w + c_e L_e + c_f L_f + c_s L_s$$

$$\text{s.t.} \quad A_{\min}, \ A_{\max}, \quad 0 \leq s_0 \leq \cdots \leq s_{n-1} \leq 1$$

Step 4: Optimize 3D Suture Points

Initially, equally spaced points

Sequential least squares (SQLSP) optimizatio Subject to constraints

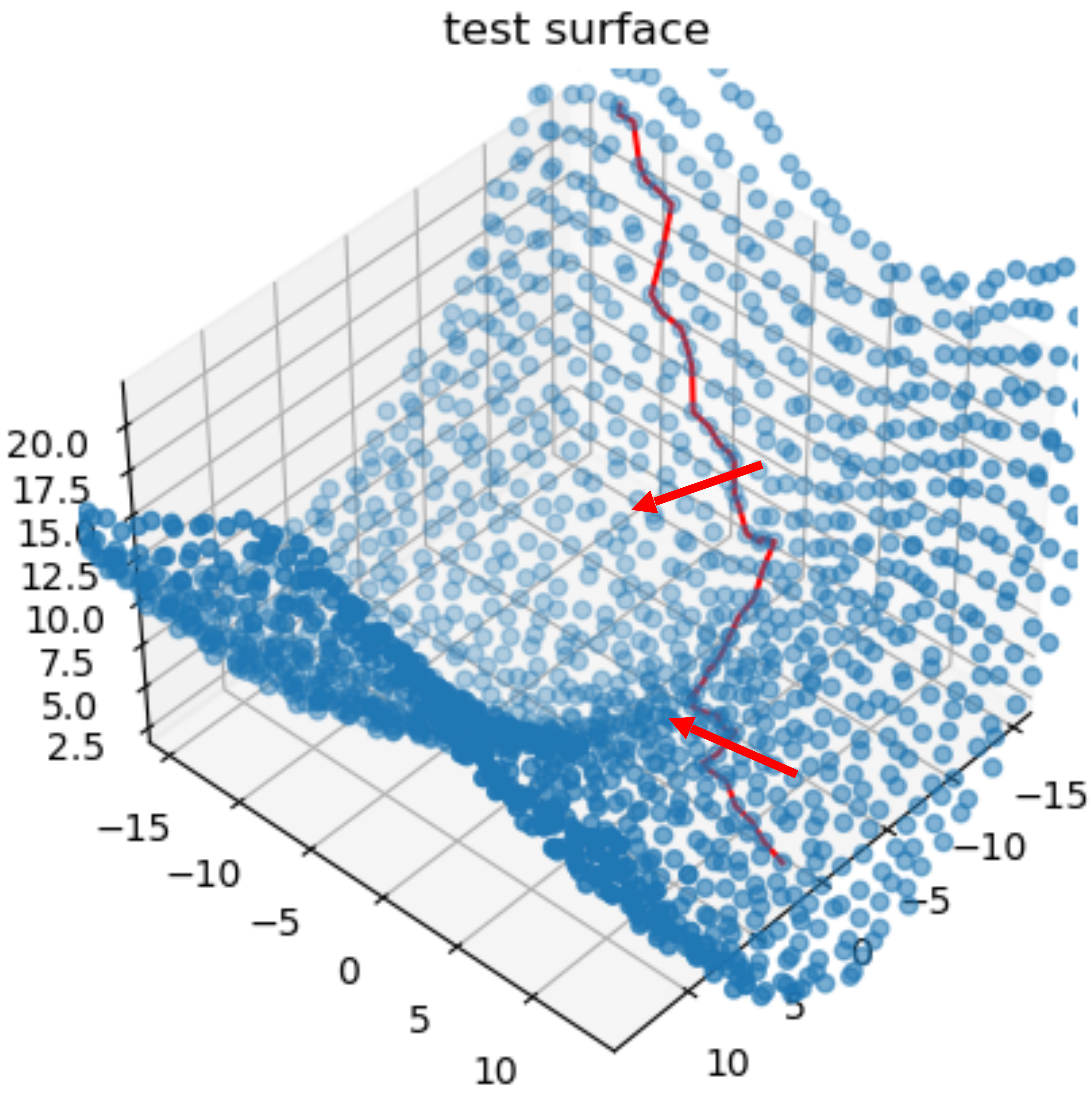


Step 4: Optimize 3D Suture Points

Move along the spline

Find nearest neighbors in 3D space

Compute Forces and adjust points in 3D using gradients



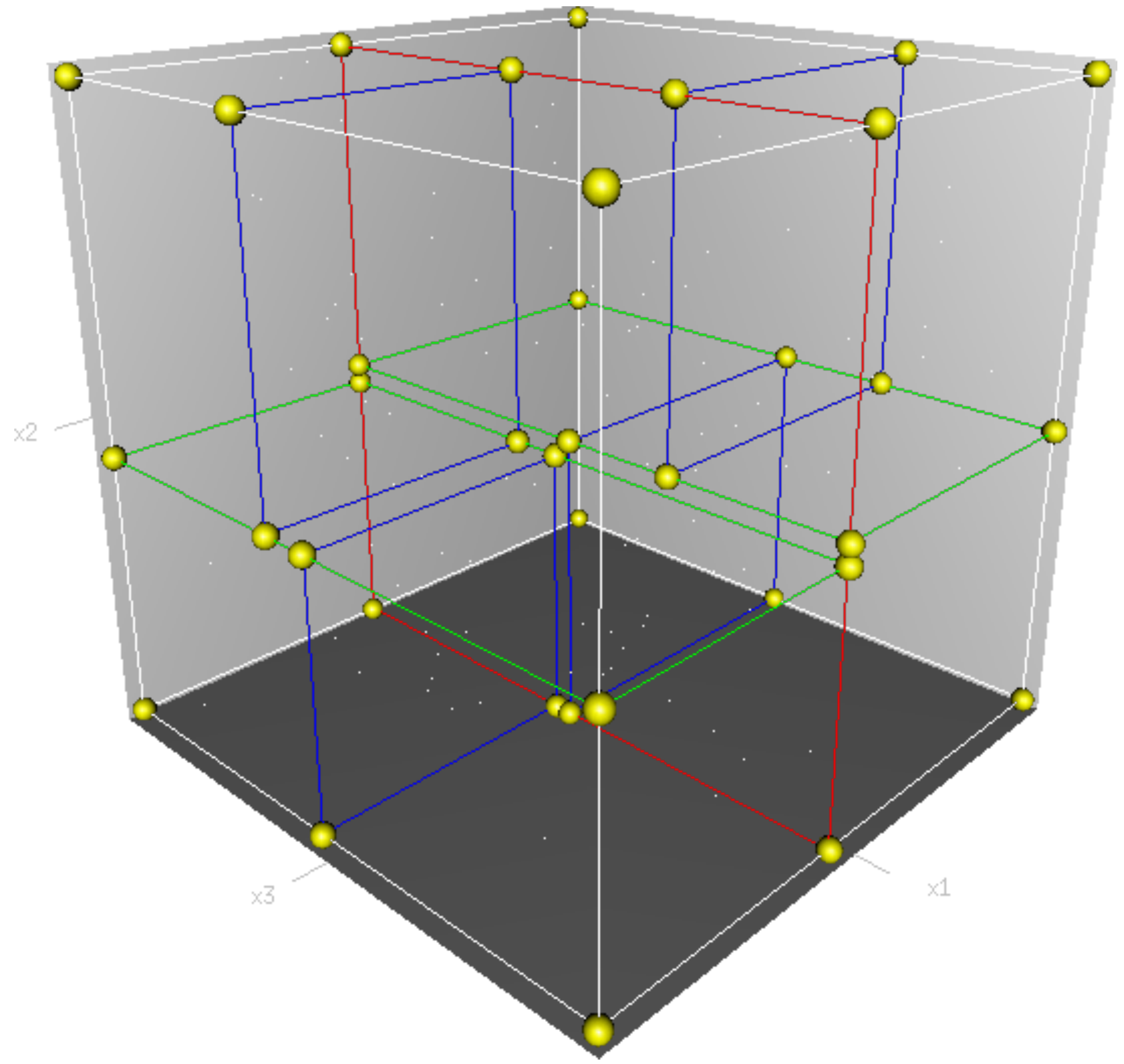
Step 4: 3D Mesh Model

Quickly find all points near a given point:

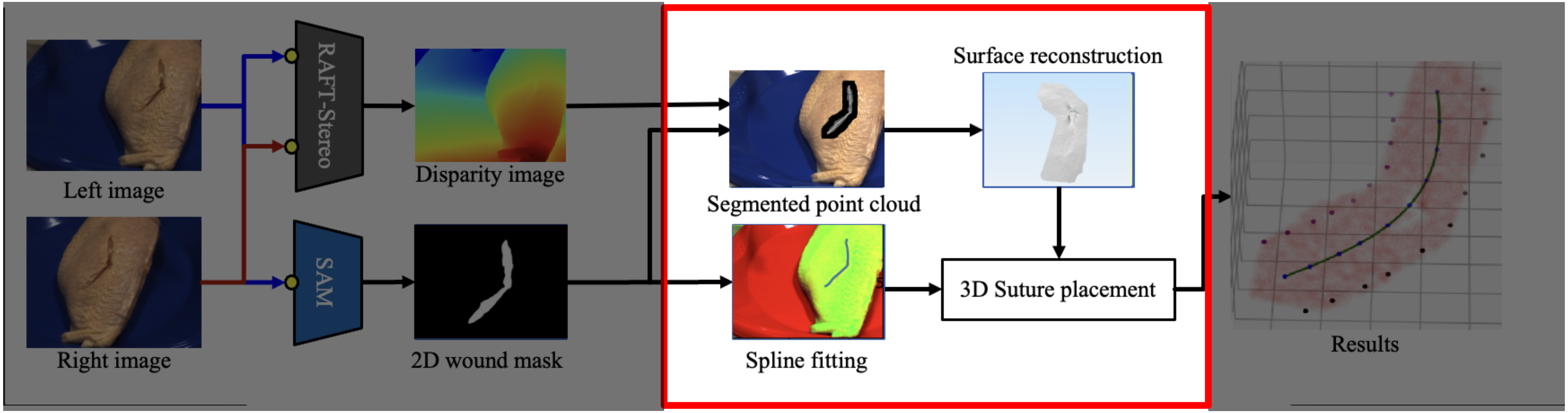
kd Tree.   O(NlogN)

M nearest-neighbors search: O(MlogN)

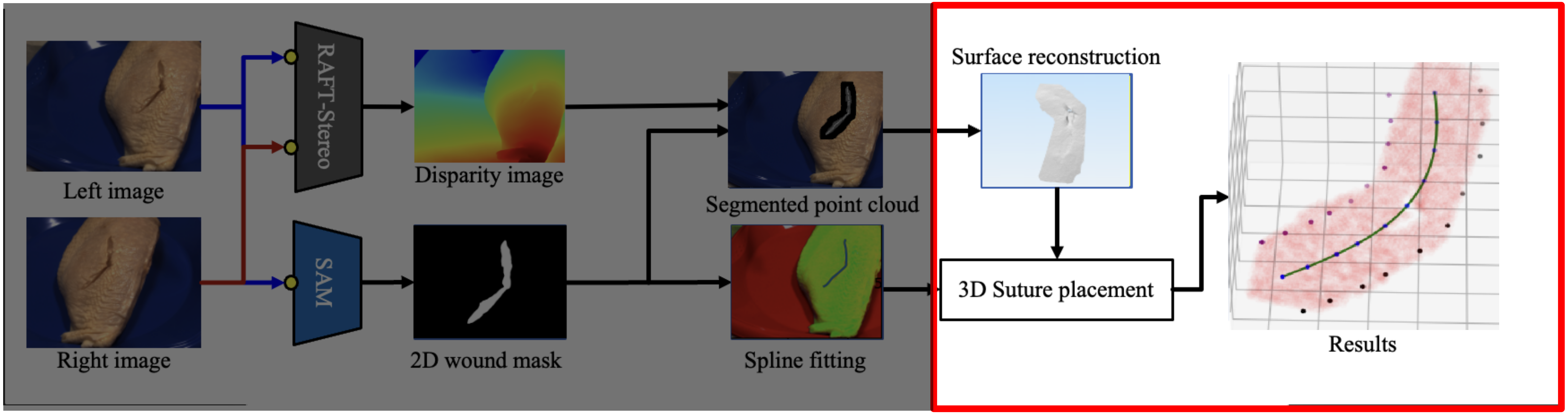
Kd Tree



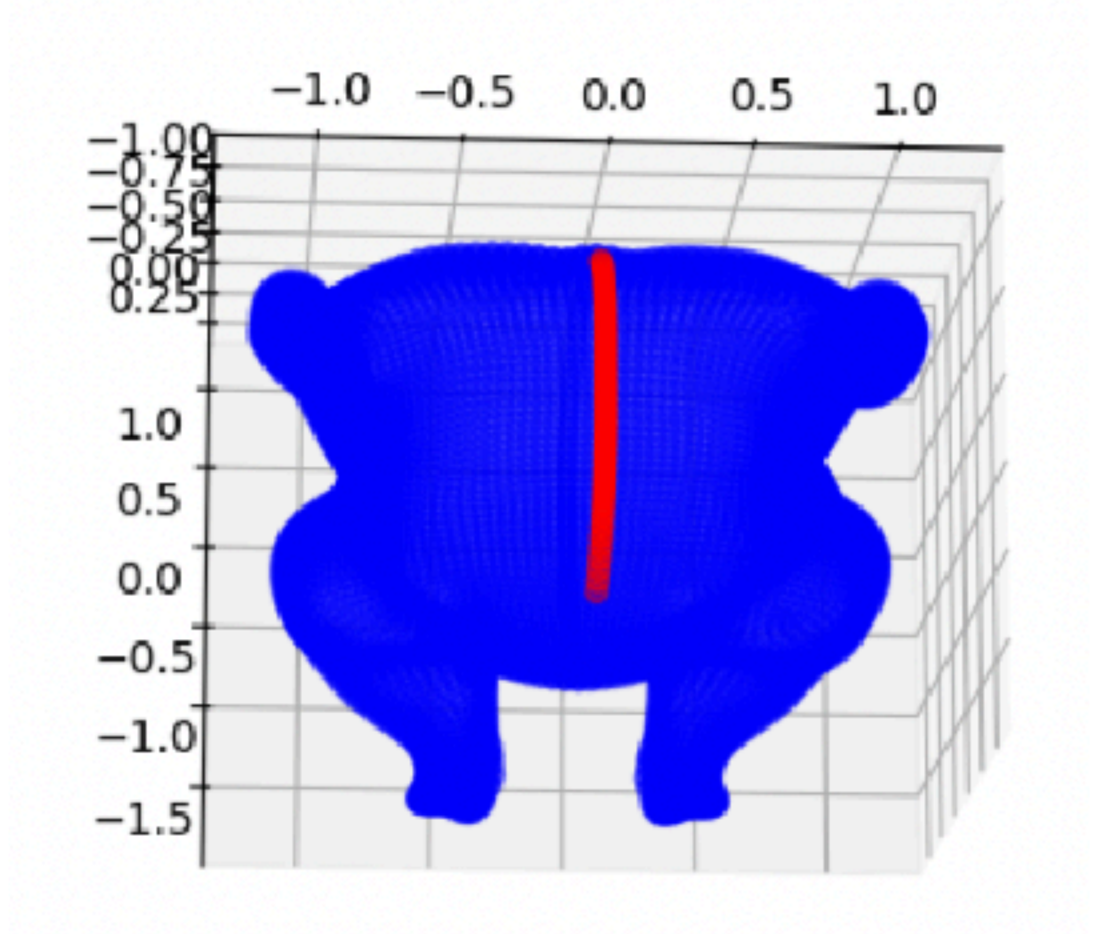
Step 4: Finalize 3D Suture Points



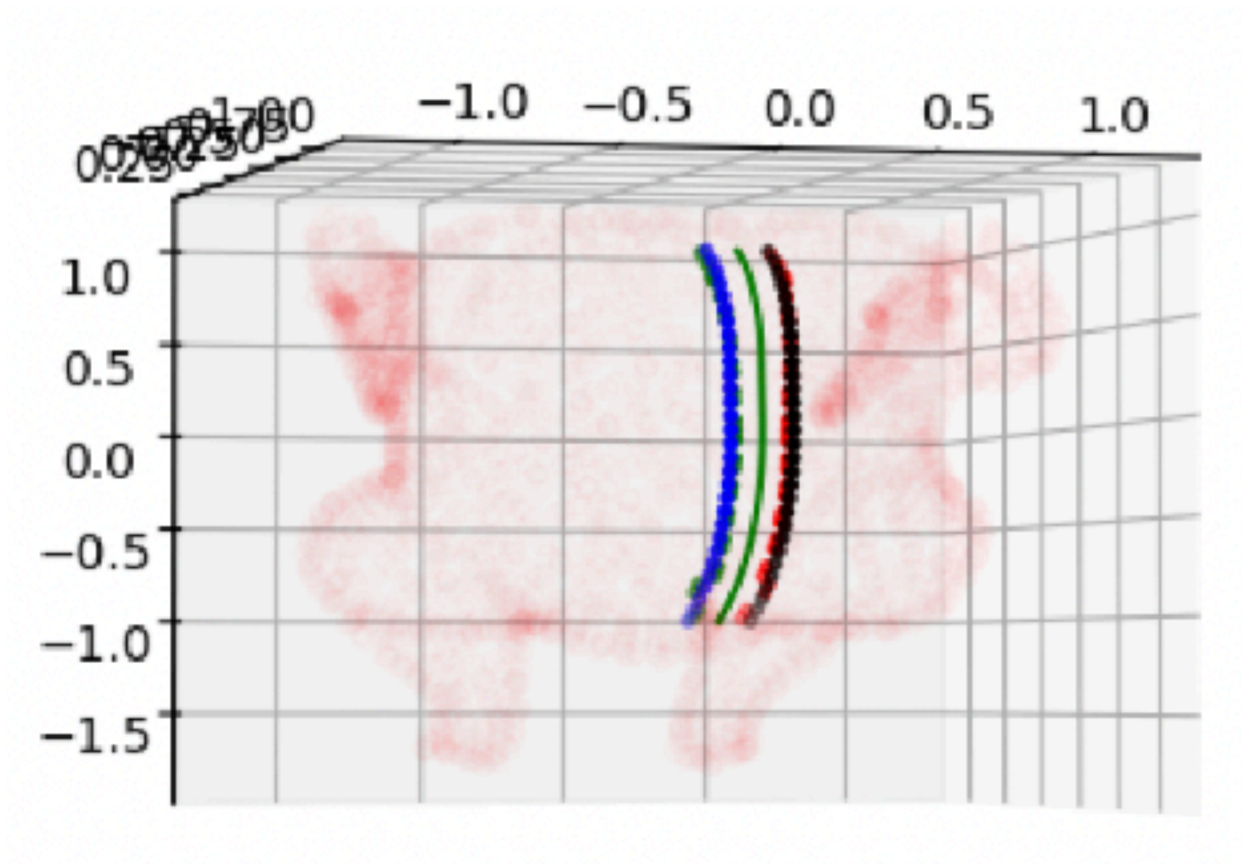
Experiments



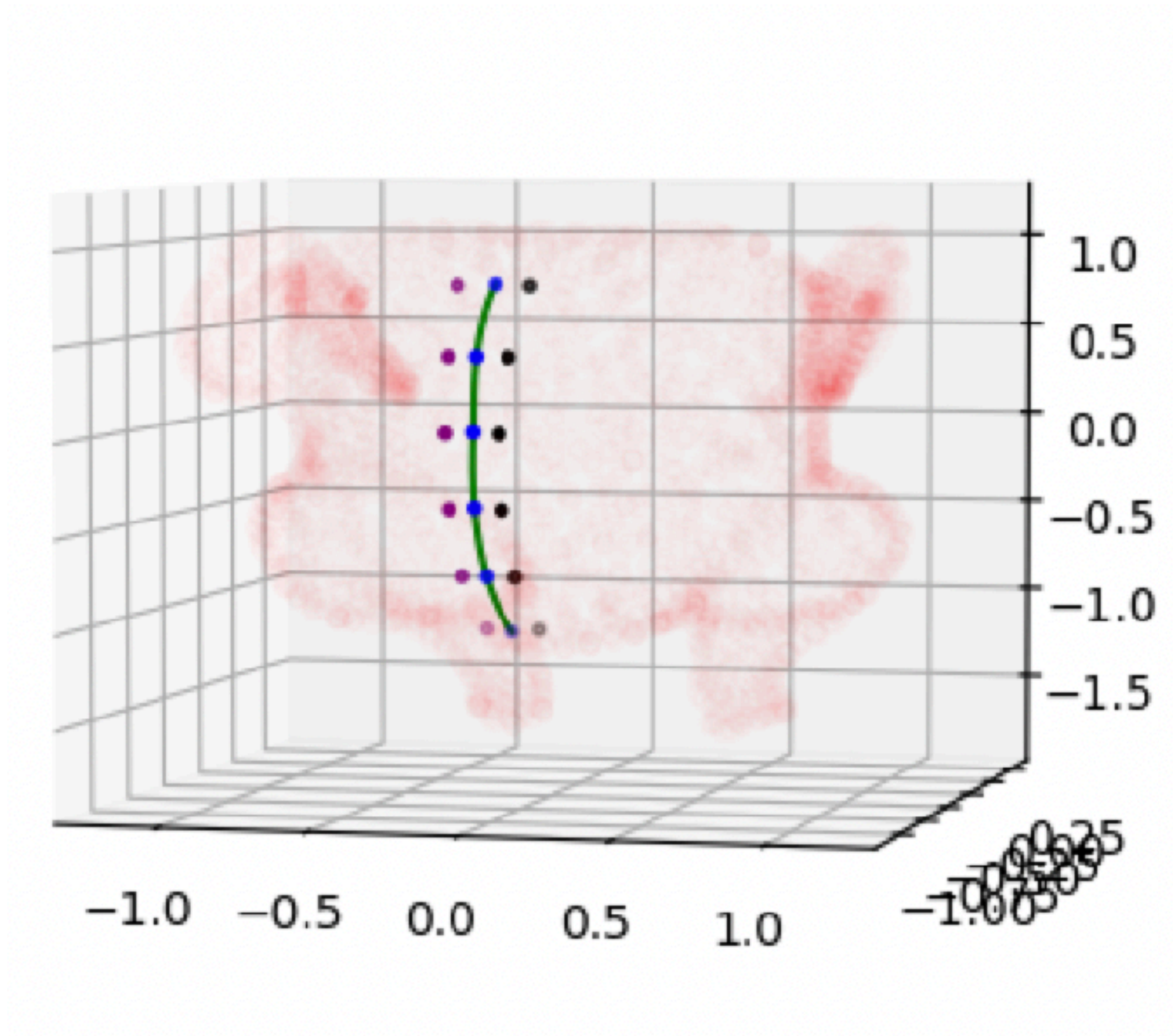
Simulation Experiment (Convex Wound)



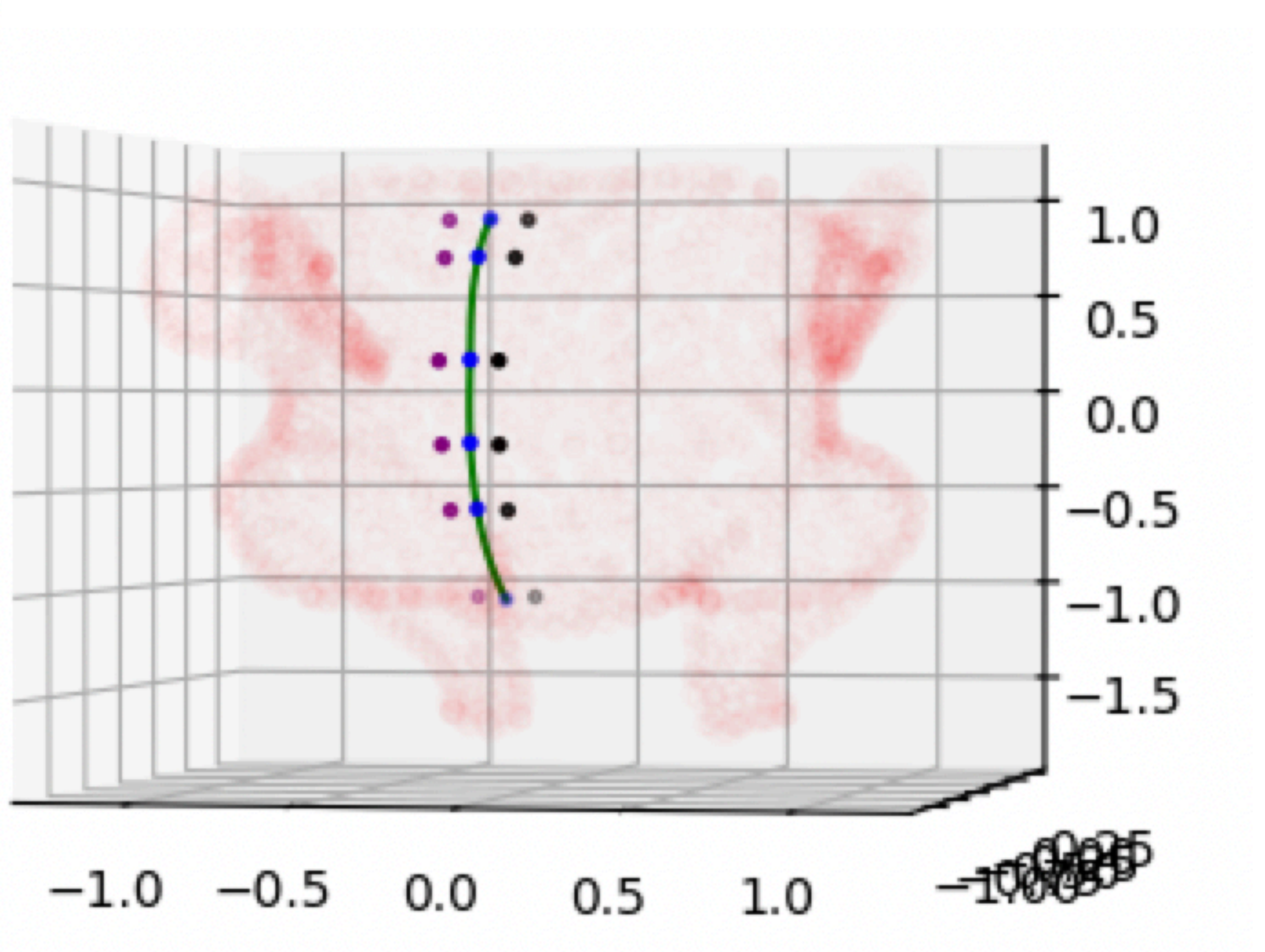
Mesh



Ribbon

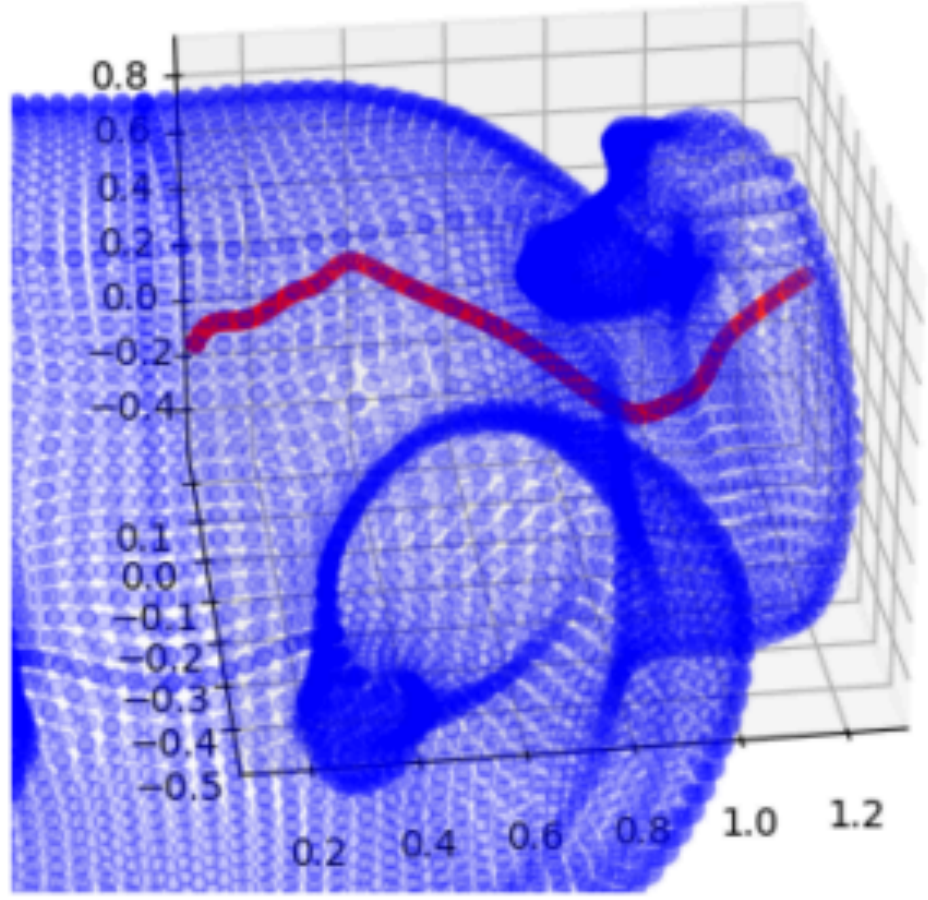


Even Baseline

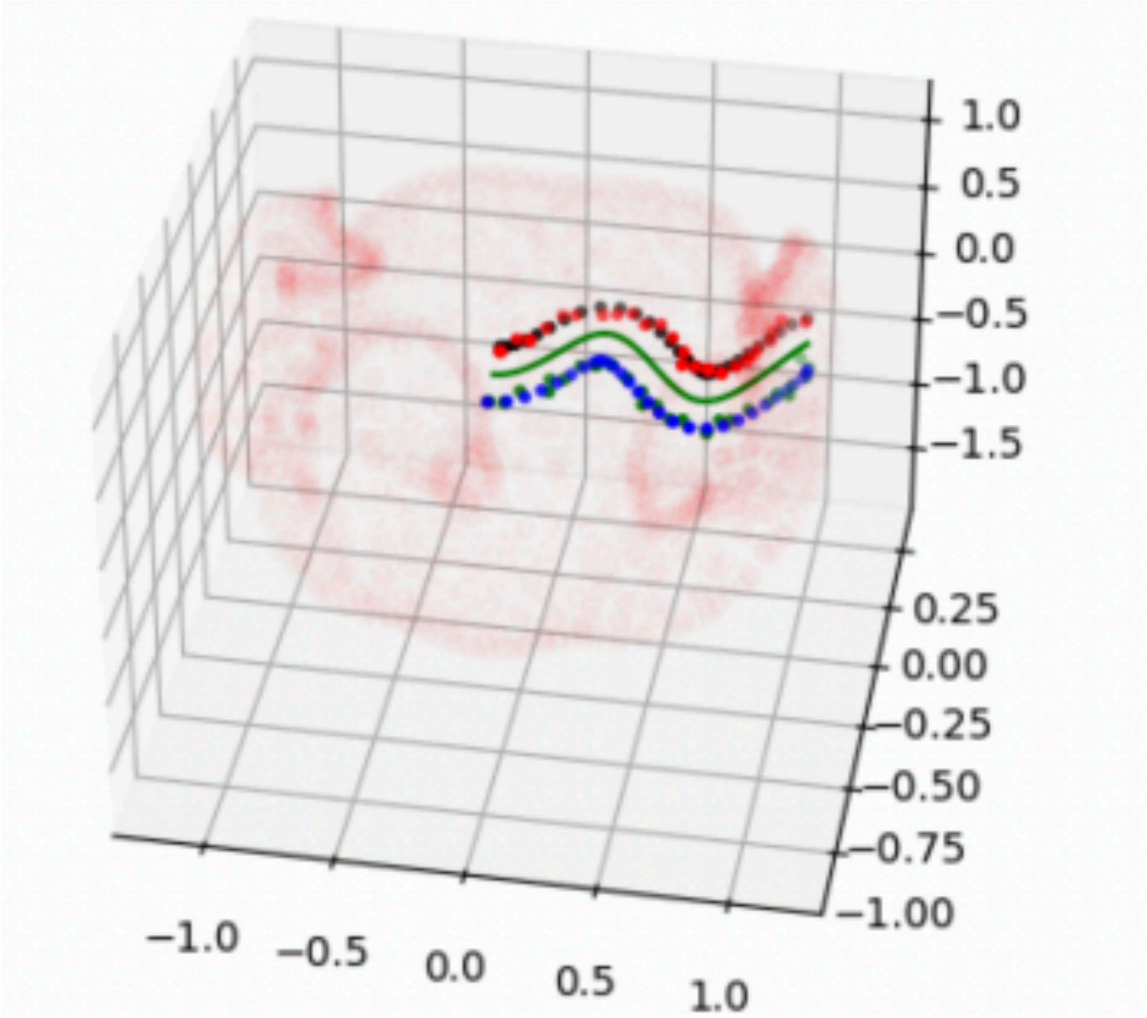


3D Suture Plan

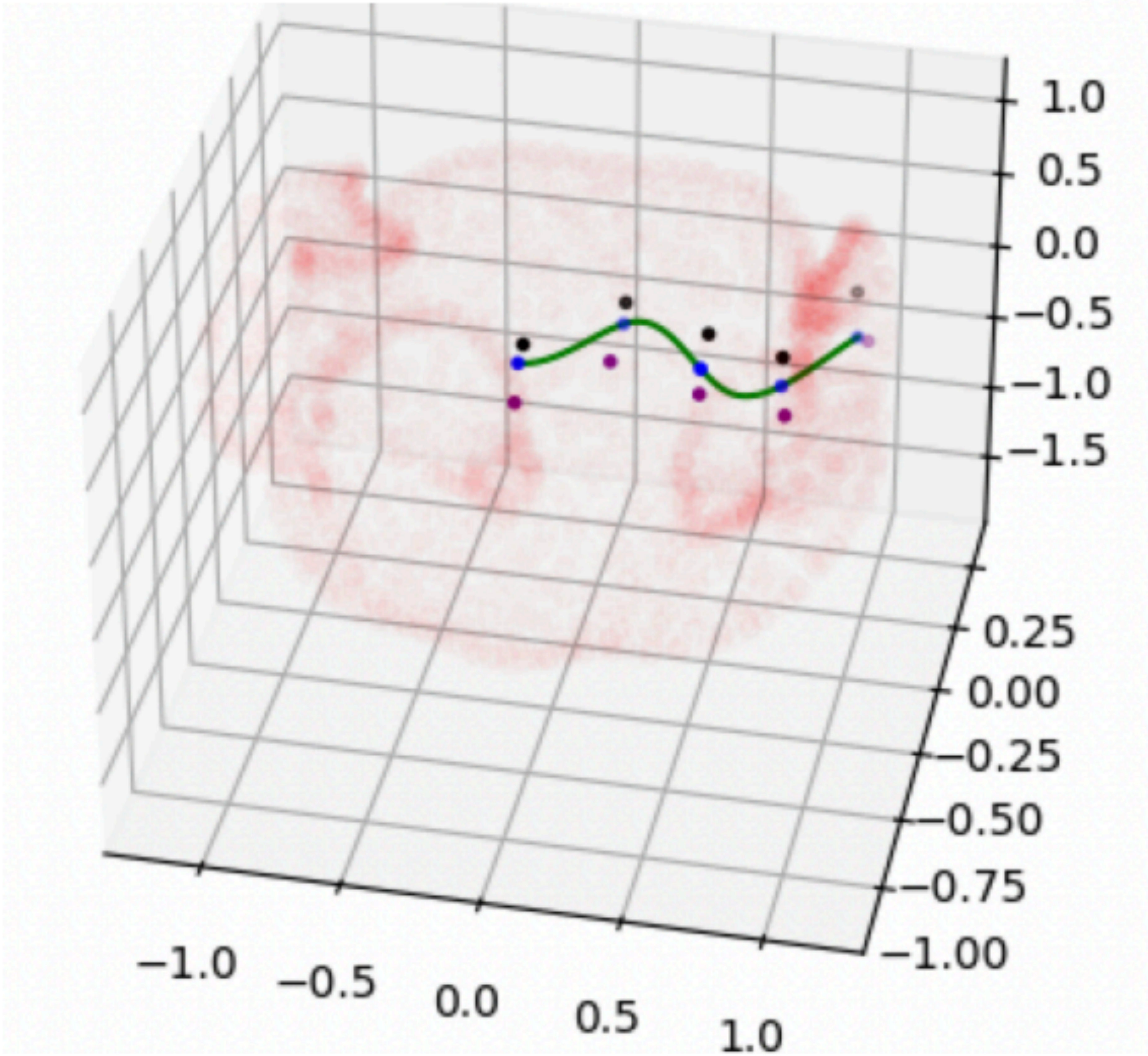
Experiments in Sim (Concave Wound)



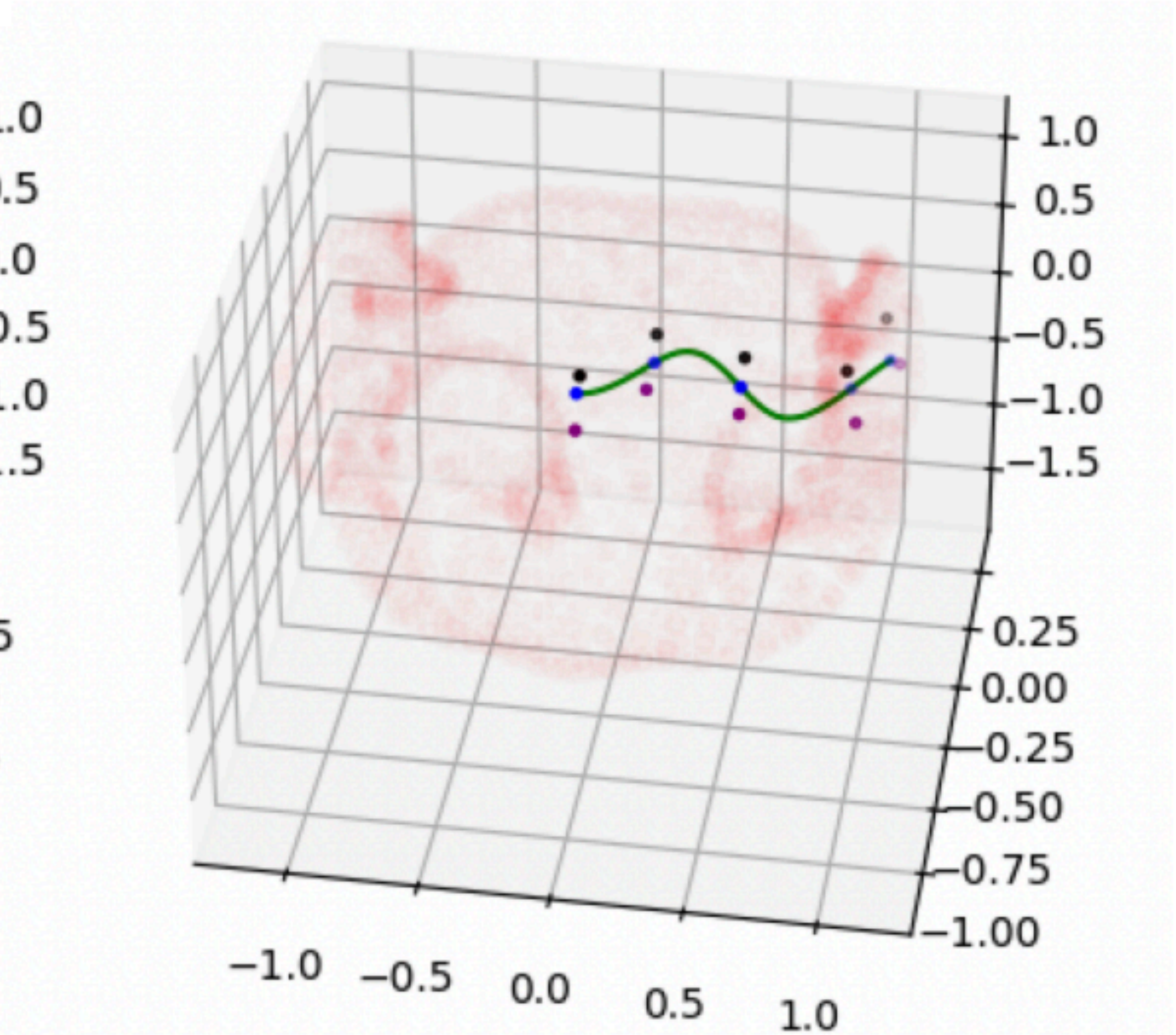
Mesh



Ribbon



Even Baseline



3D Suture Plan

Physical Experiments

Compare:

1) SP**2D**EEF algorithm

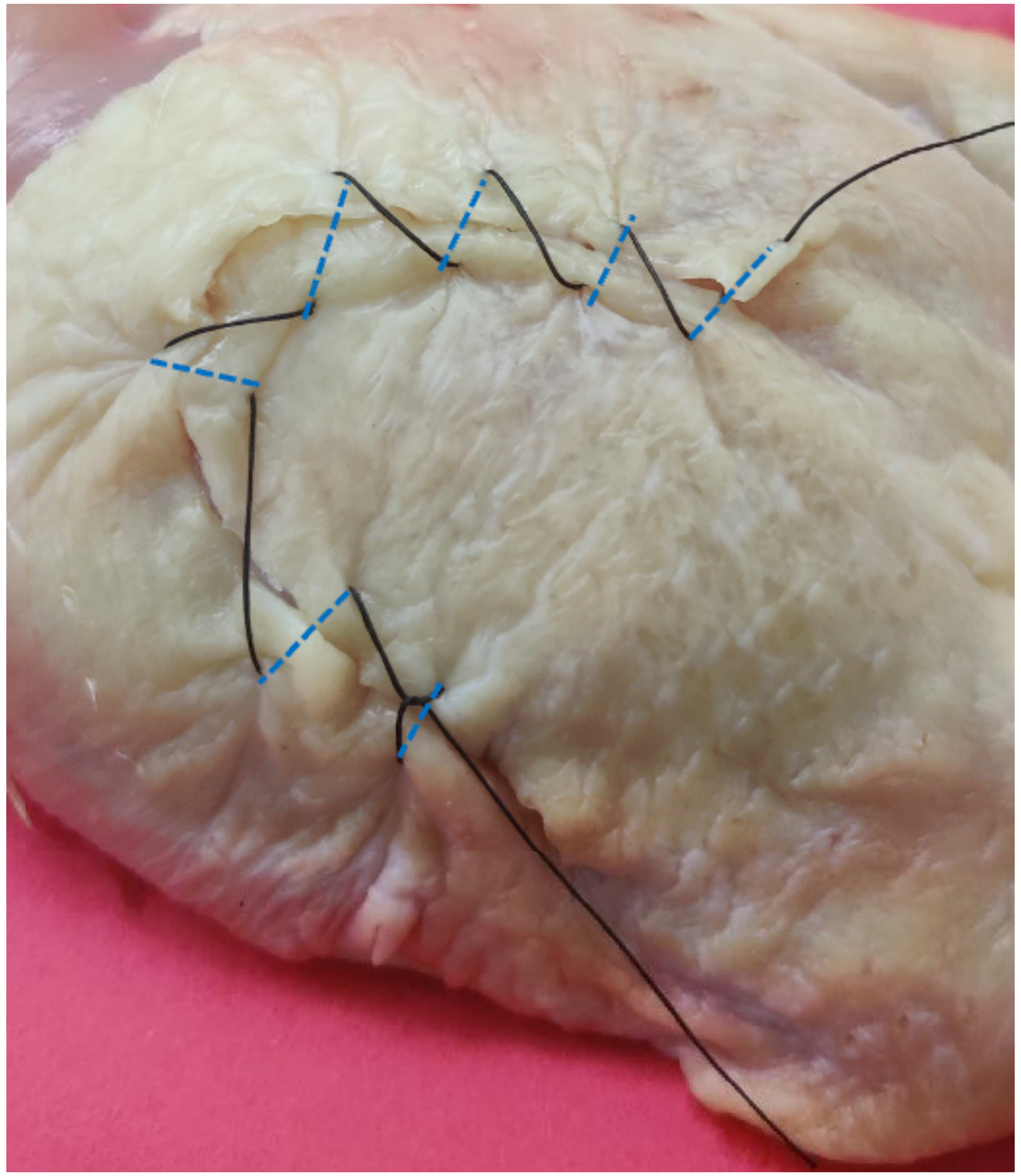
2) Uniform Spacing baseline

3) SP**3D**EEF algorithm

Physical Experiments

(Thumbtacks to indicate placement)

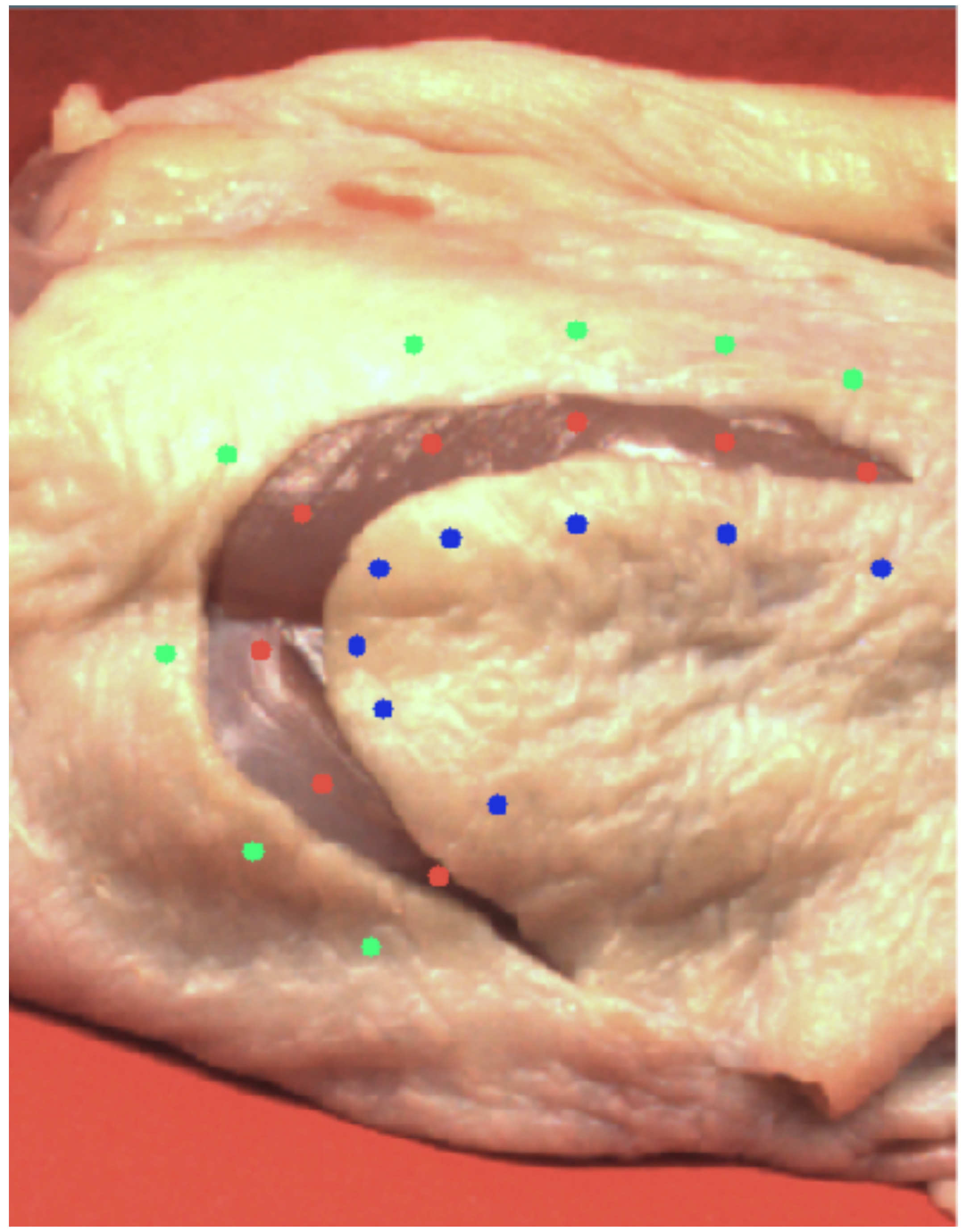
Planned 3D Sutures



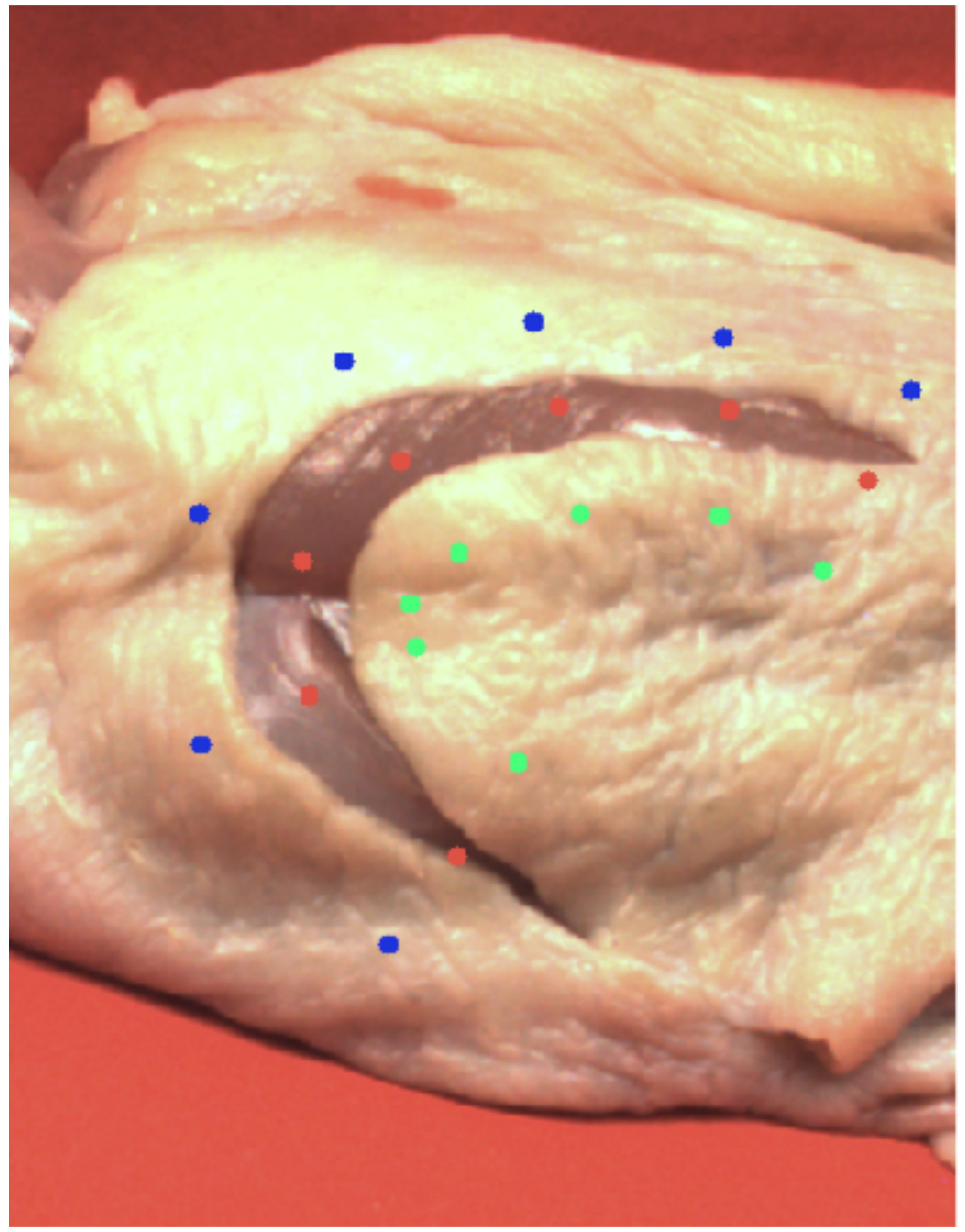
Sutured Wound

Physical Experiments

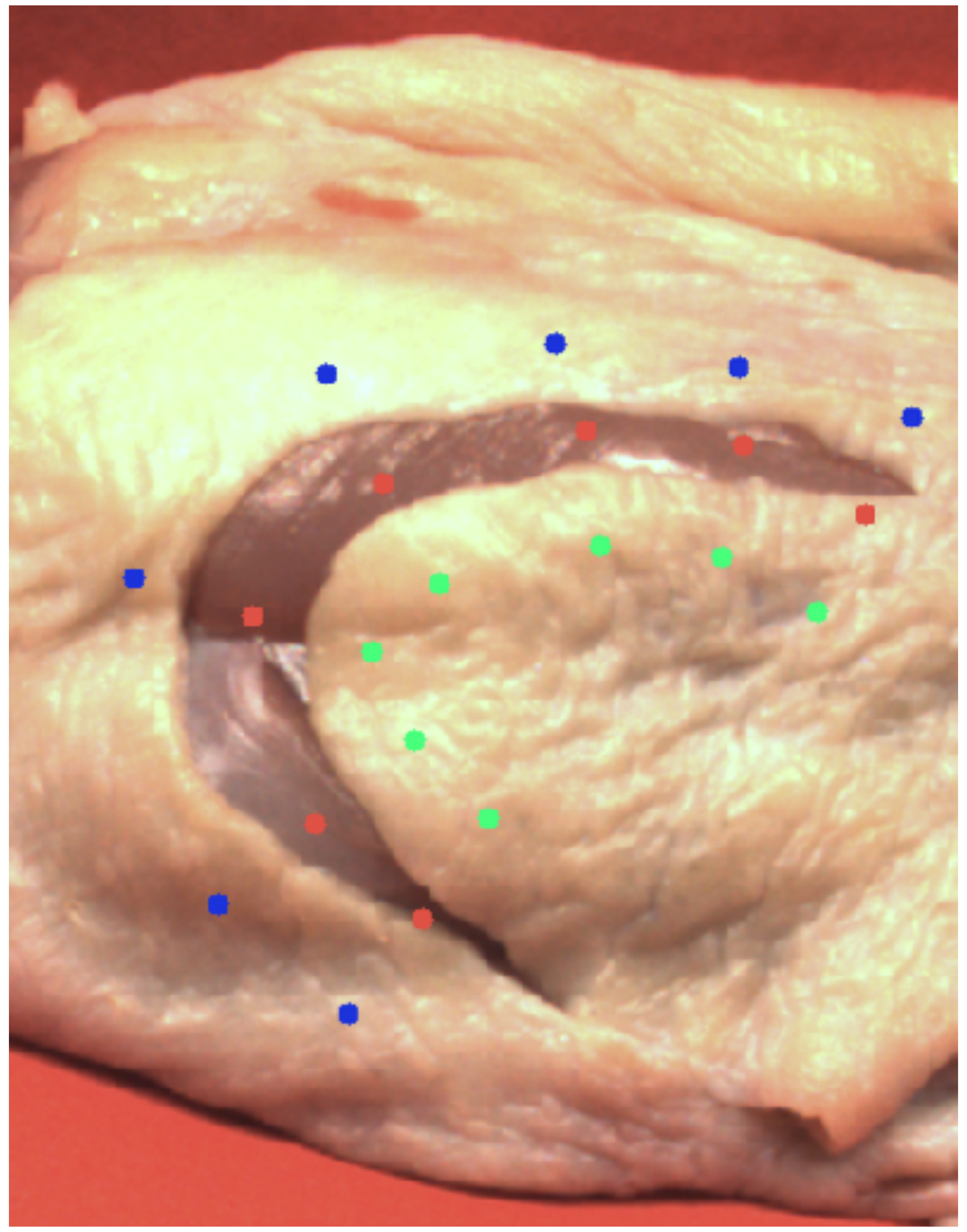
Original



2D Suture Plan



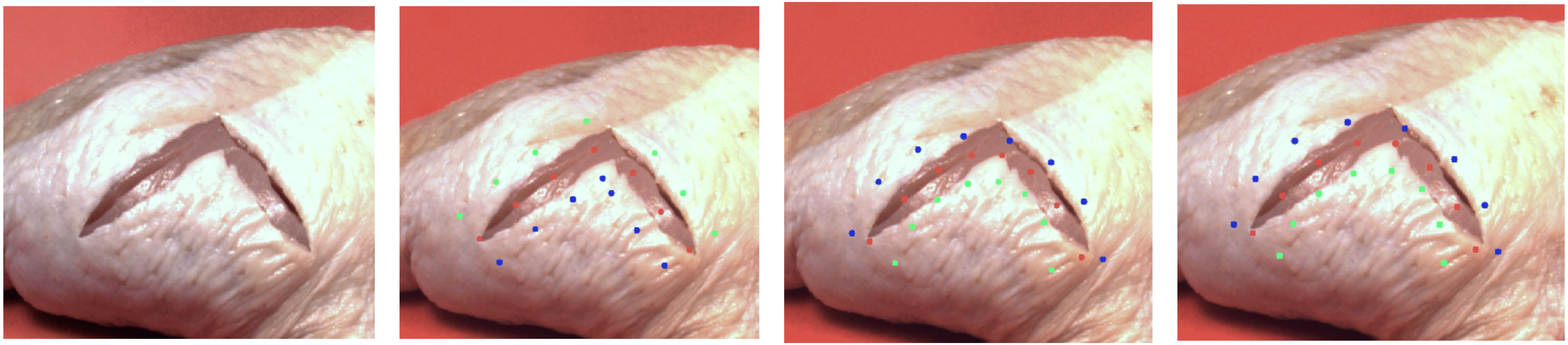
Even Baseline



3D Suture Plan

Physical Experiments

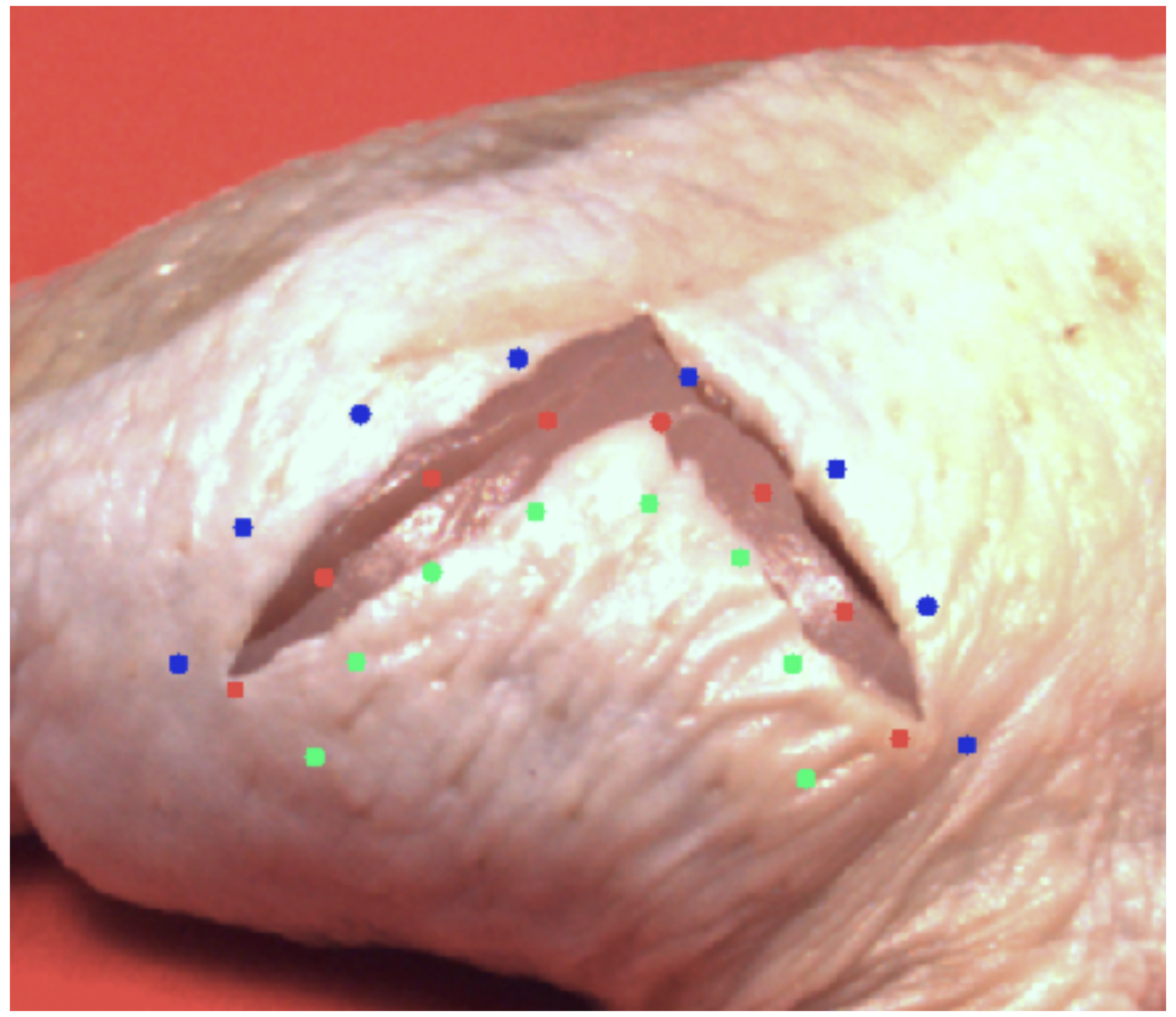
3D spline cannot fit to sharp corner:



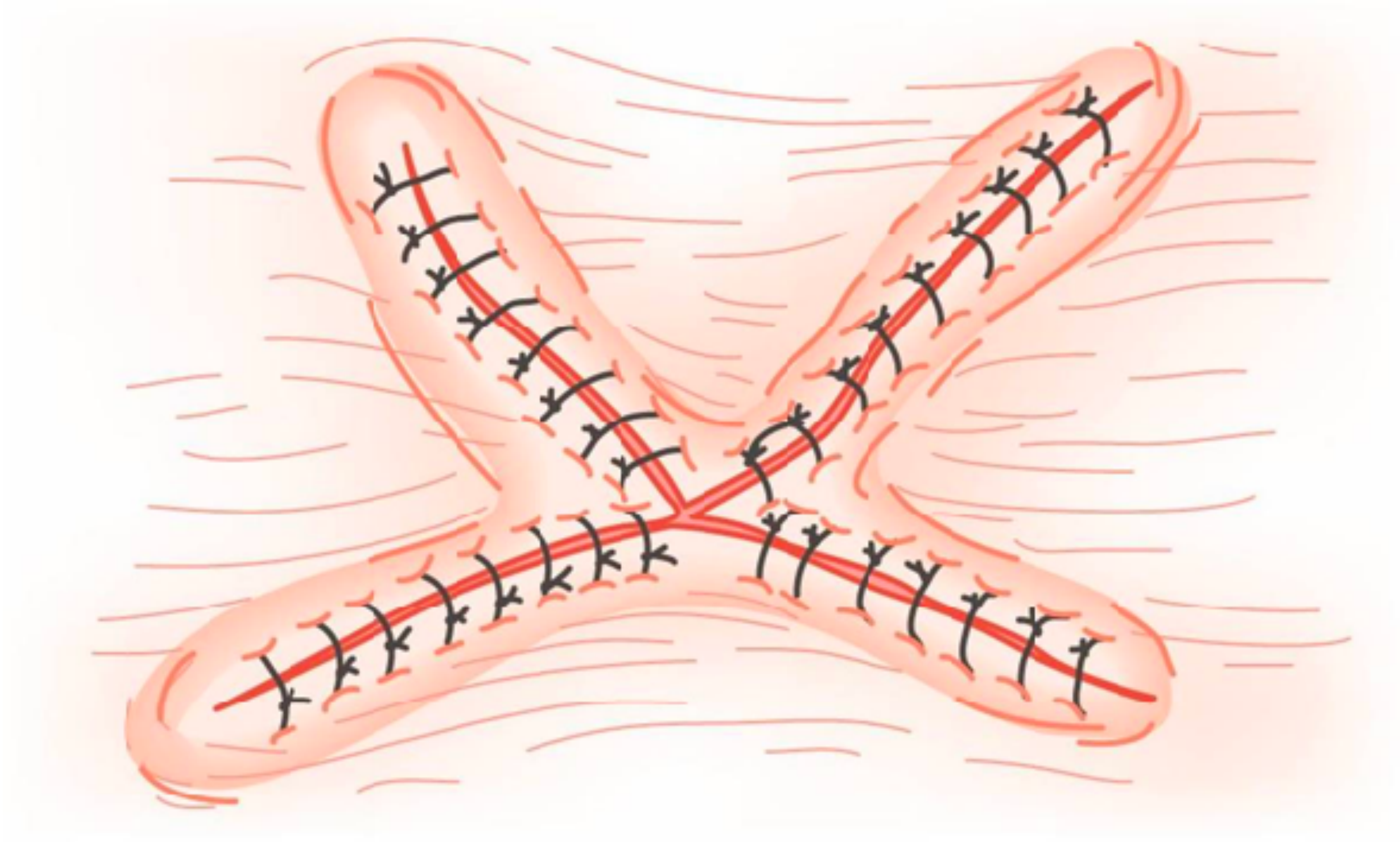
Original | 2D Suture Plan | Even Baseline | 3D Suture Plan

Future Work

3D Wounds with corners

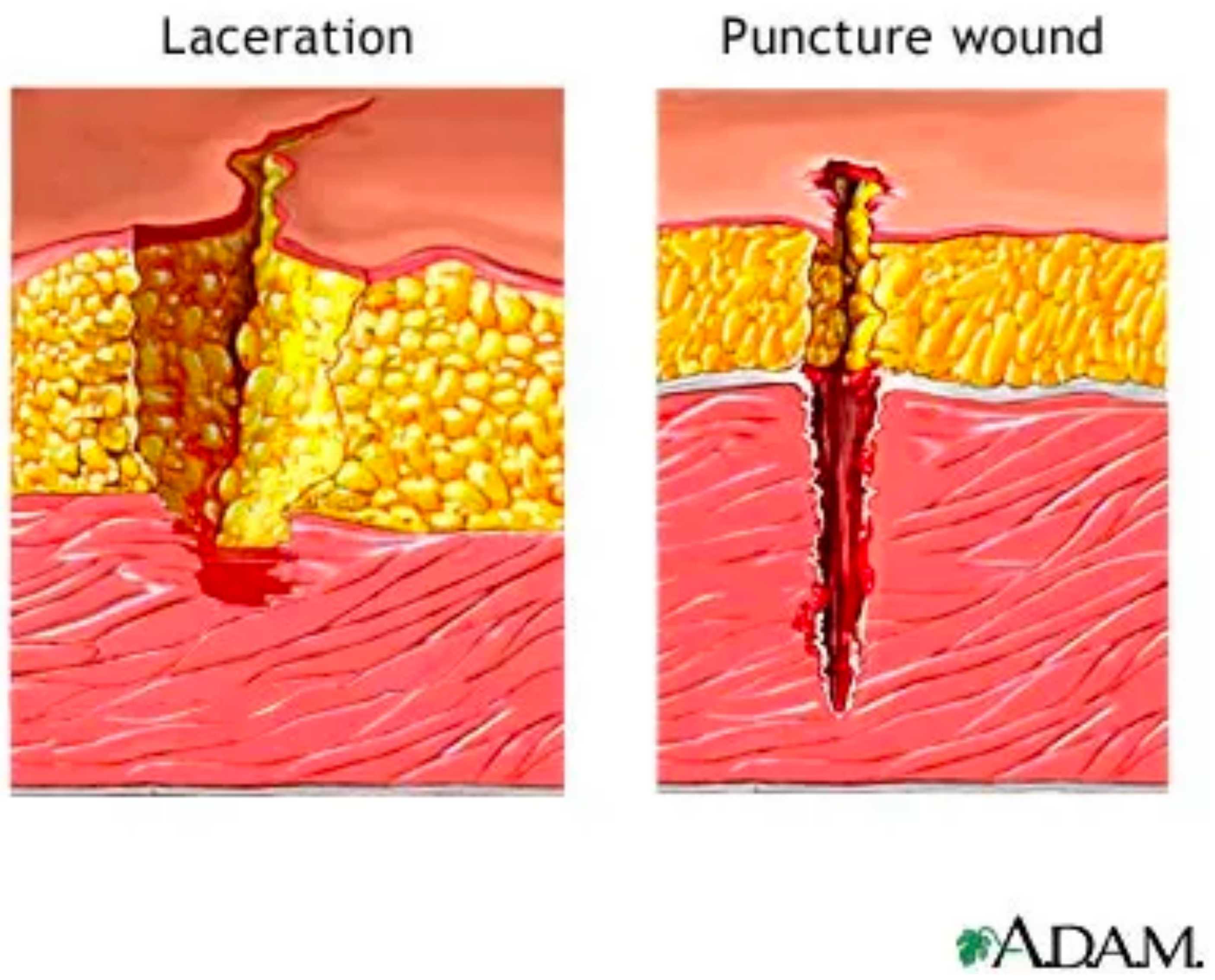


3D Wounds with branches



https://doctorlib.info/medical/tintinalli-emergency-medicine/12.html

3D Wounds with Variable depth

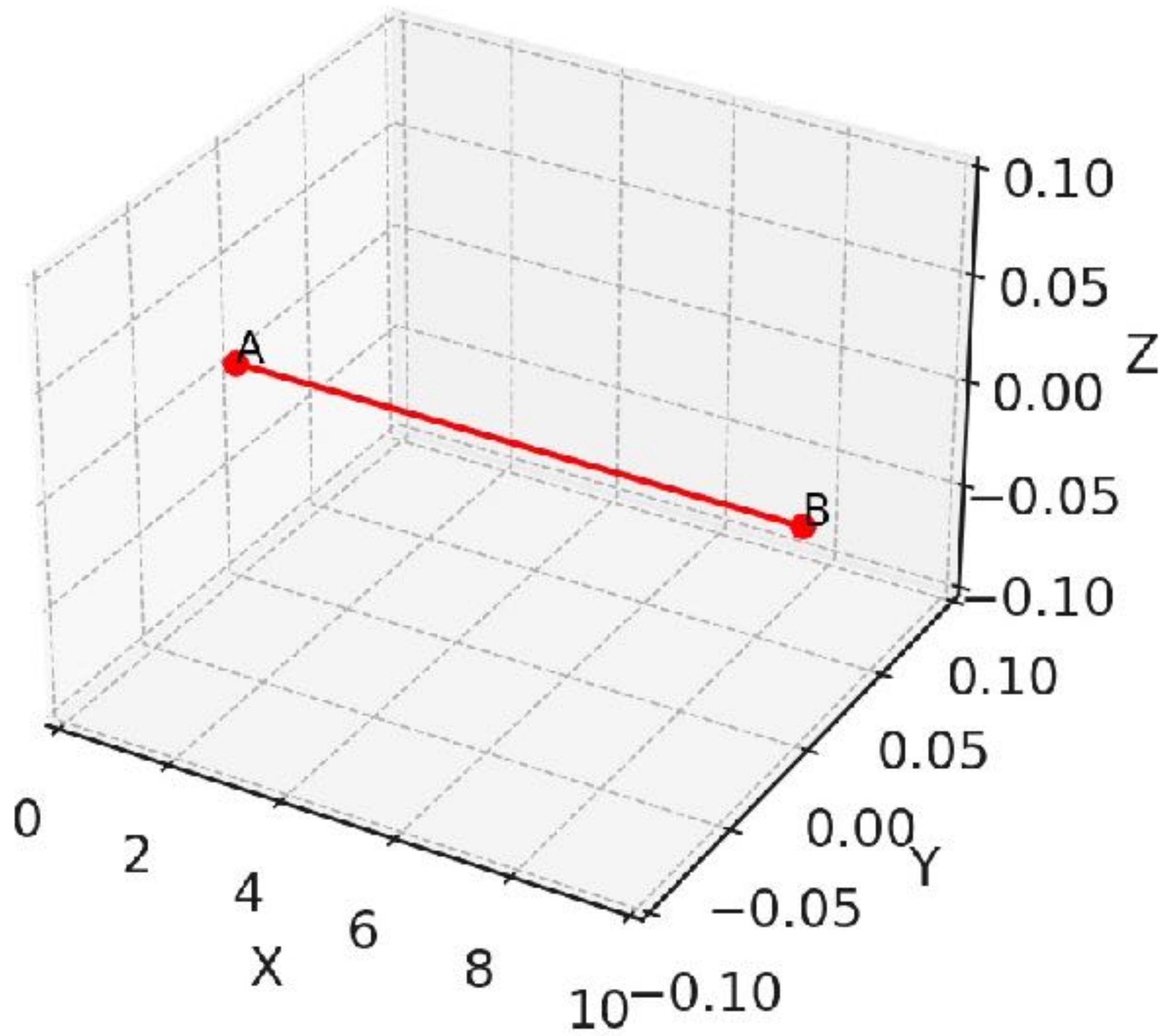


https://www.orthopaedics.com.sg/treatments/orthopaedic-surgeries/laceration-wound/

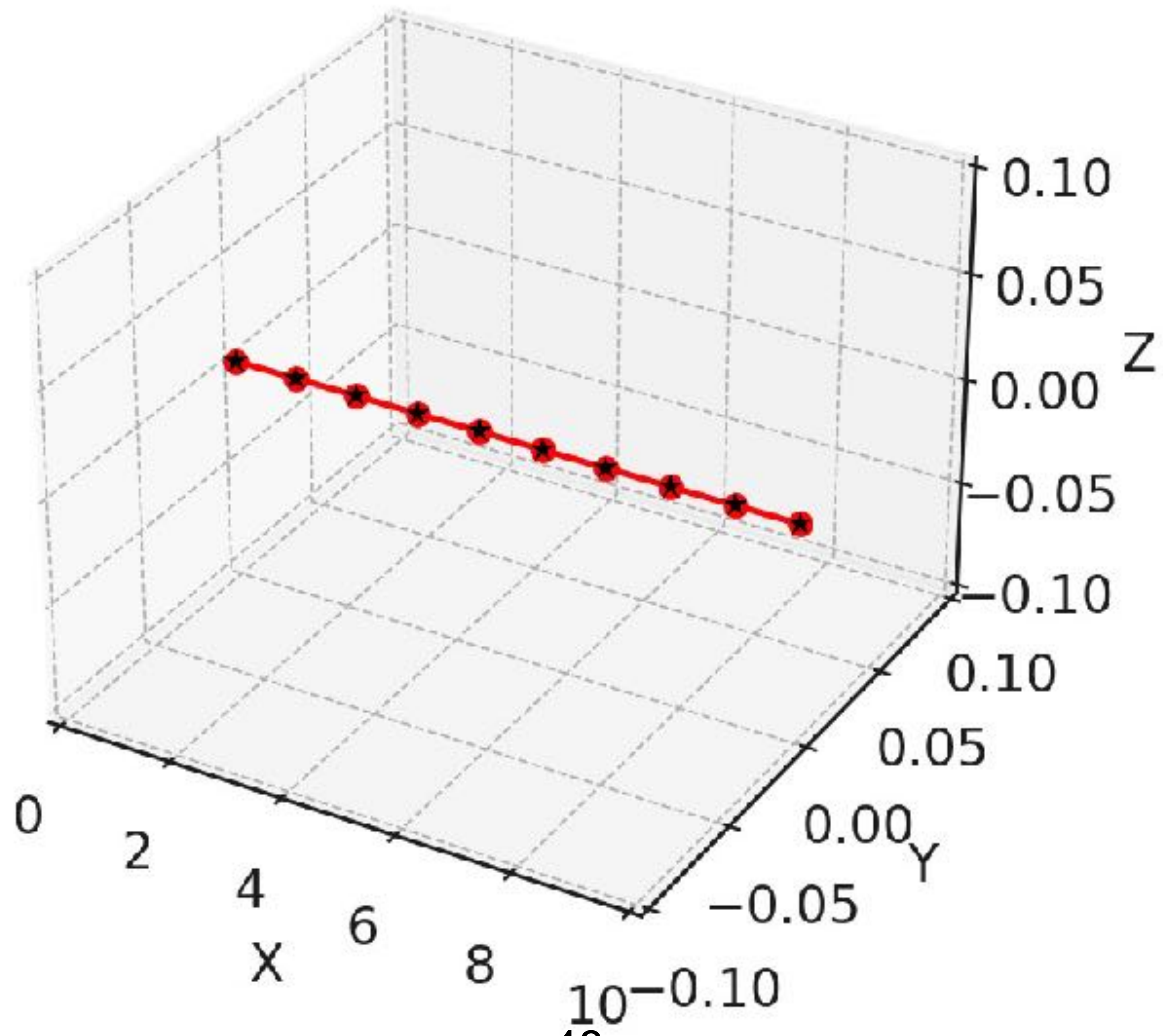
Future Work

Surgeon Spline Adjustment

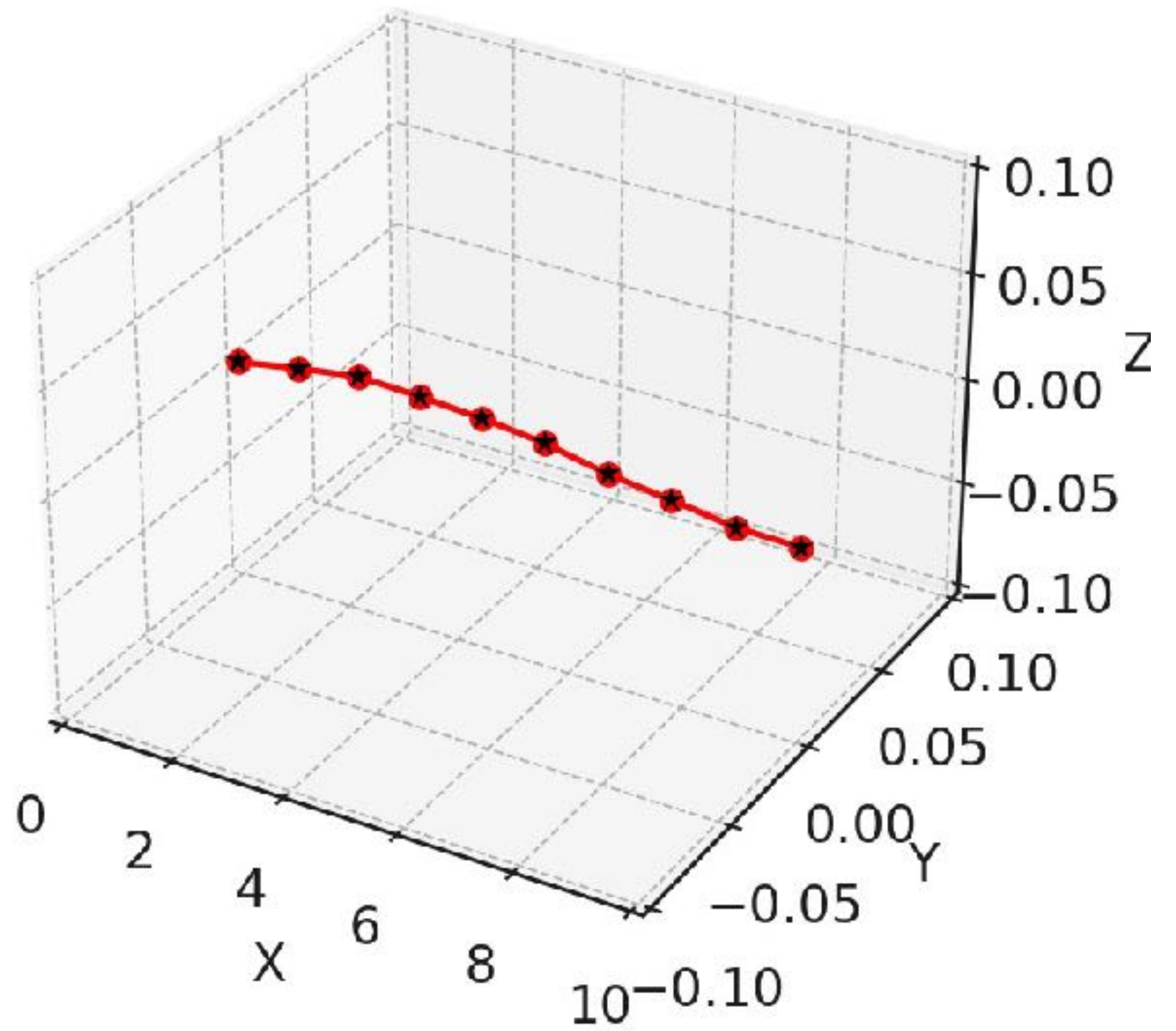
1. surgeon clicks 2 wound endpoints



2. System fits linear spline

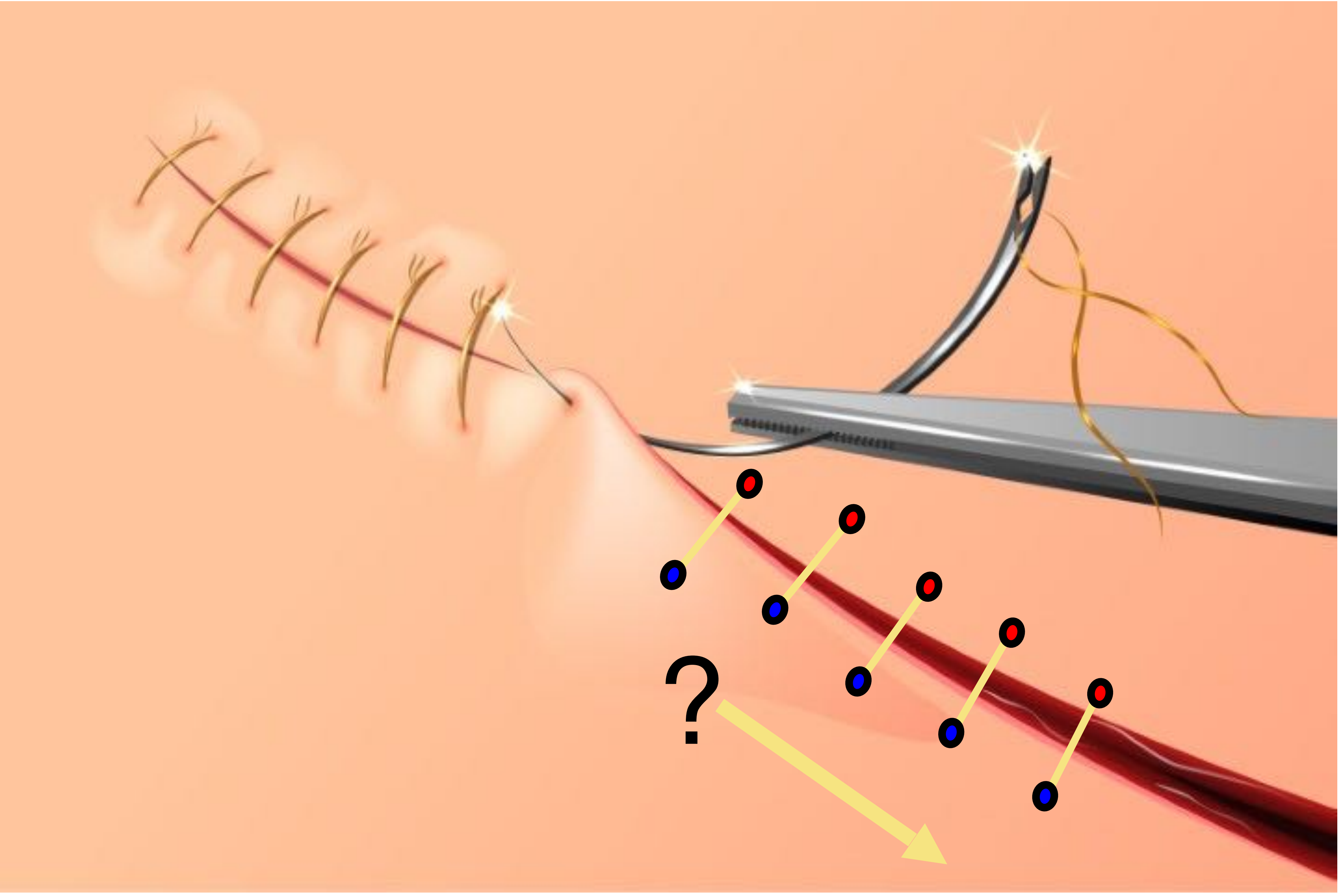


3. Surgeon adjusts spline points

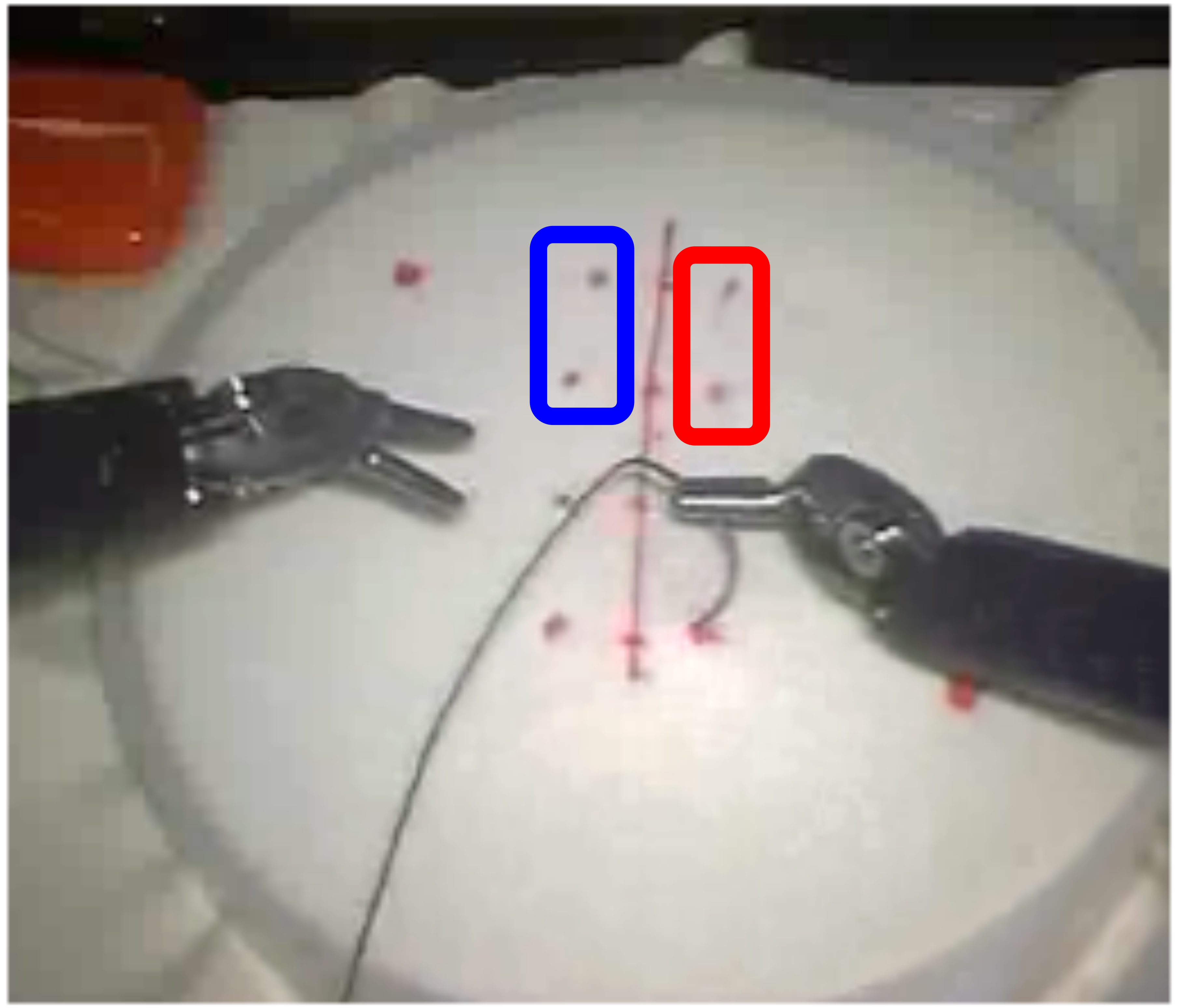


Future Work

Online Suture Re- Planning



Augmented Reality Display



Automating **3D** Surgical Suture Planning

Viraj Ramakrishnan*, Julia Isaac*, Harshika Jalan, Harsha Polavaram, Hansoul Kim, Aviv Adler, Danyal M Fer, Ken Goldberg

Contributions:

1) First application of Meta Segment Anything Model (SAM) to segment a human wound from an image.

2) Extend SP2DEEF algorithm to compute suture plans for 3D non-linear wounds

3) Physical experiments

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* denotes equal contribution