CAMERA POSE ESTIMATION FROM SURGICAL VIDEOS WITH DEEP LEARNING

PROJECT N°7

STUDENTS: Andrea Naclerio

Ali Shadman Yazdi

Siavash Taleghani

TUTOR: Alberto Rota

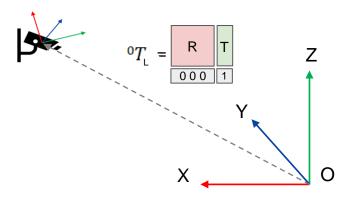
Camera Pose Estimation

What is camera pose estimation?

A homogeneous transformation matrix that describes position and orientation of a camera

Why do we need camera pose?

- 3D reconstruction
- Enhanced perception
- Organs and lesions localization



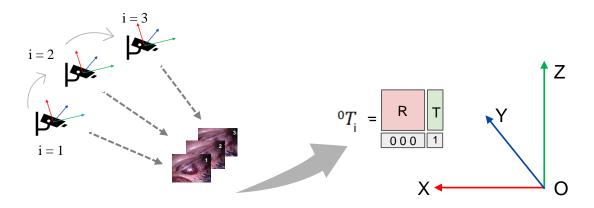
State of the art

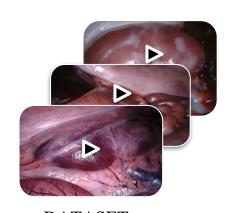
Visual SLAM

- Tracking points of interest
- 3D positioning through triangulation
- Developing 3D map
- Mainly used in car localization

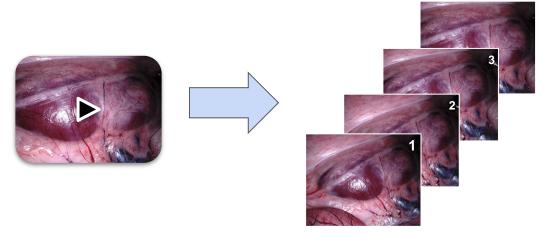
Deep Learning

- Feature extraction through DCNN
- Camera pose and image information relationship establishment
- Predicting camera pose

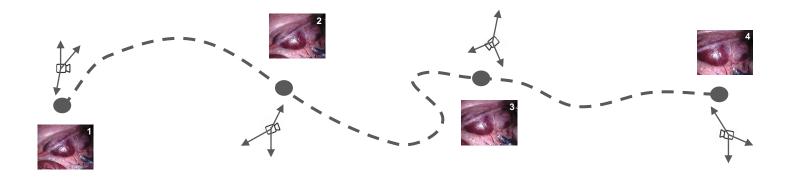


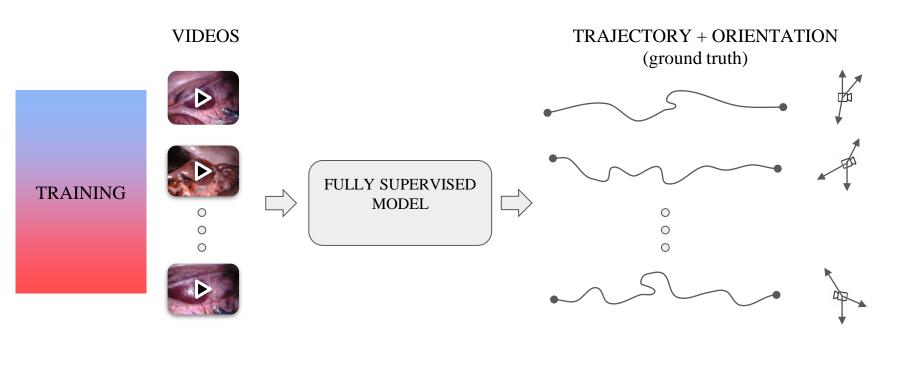


DATASET
27 monocular videos
annotated

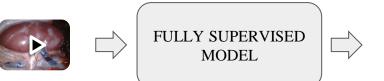


FRAMES



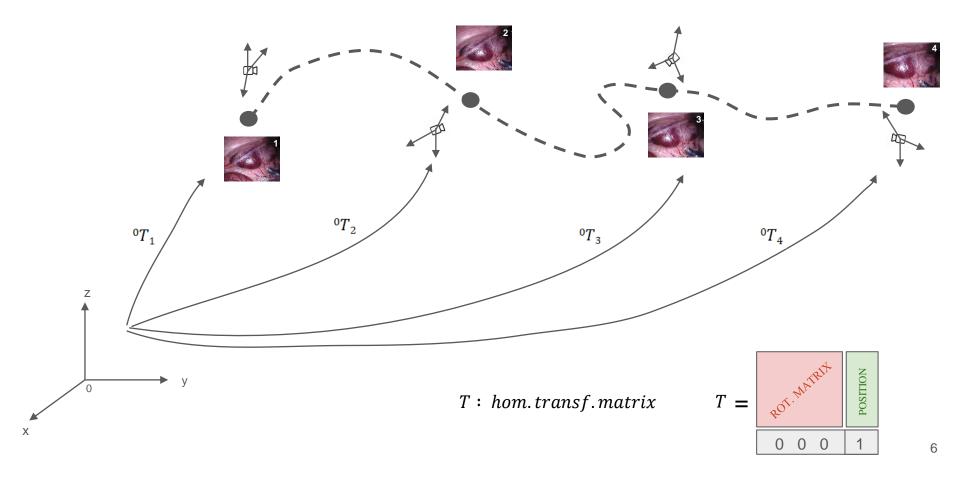




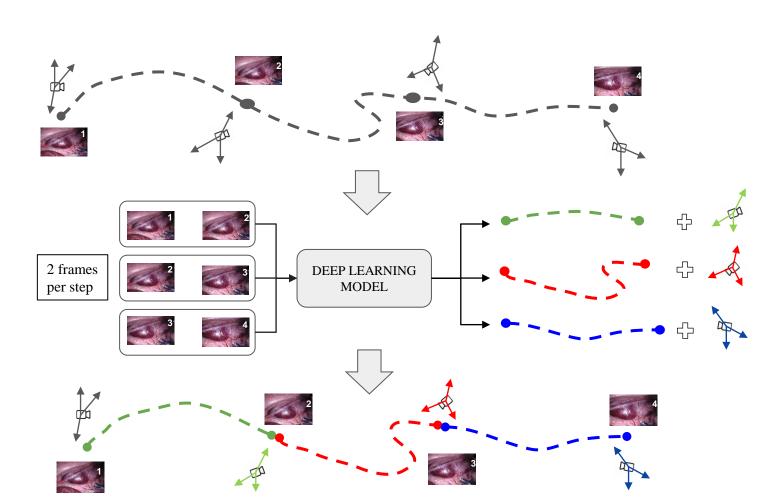




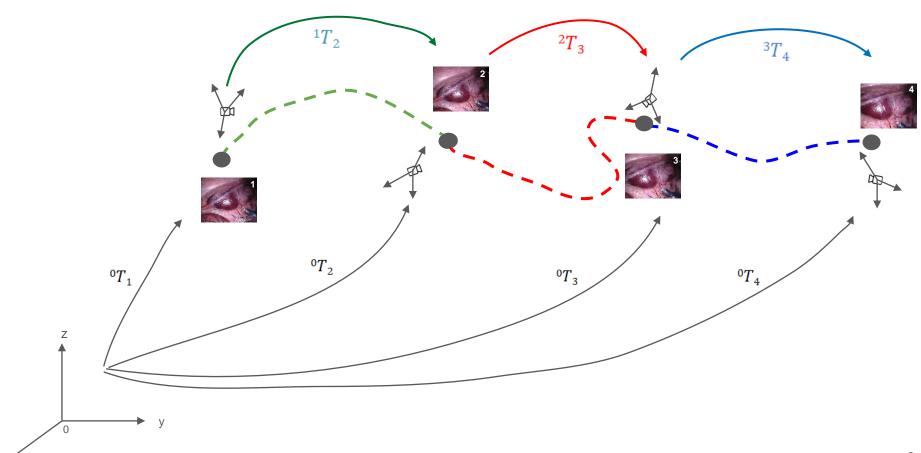
Ground-Truth data



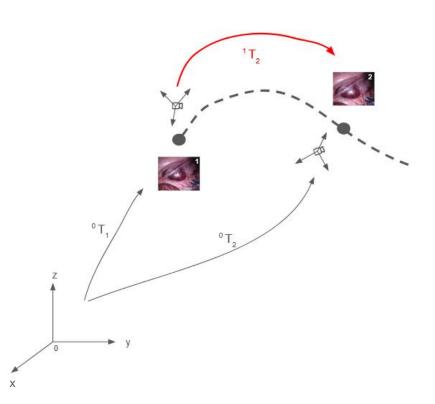
Problem decomposition

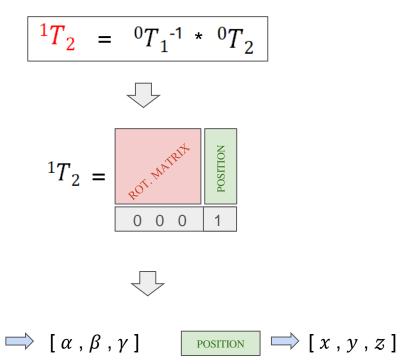


New transformation matrix

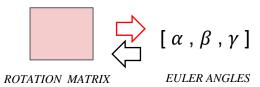


Output computation





INVERSE PROBLEM



$$R_{x,y',z''}(\alpha,\beta,\gamma) = \begin{bmatrix} c\beta c\gamma & -c\beta s\gamma & s\beta \\ s\alpha s\beta c\gamma + c\alpha s\gamma & -s\alpha s\beta s\gamma + c\alpha c\gamma & -s\alpha c\beta \\ -s\beta c\alpha c\gamma + s\alpha s\gamma & s\beta c\alpha s\gamma + s\alpha c\gamma & c\alpha c\beta \end{bmatrix} \qquad R = \begin{bmatrix} r11 & r12 & r13 \\ r21 & r22 & r23 \\ r31 & r32 & r33 \end{bmatrix}$$

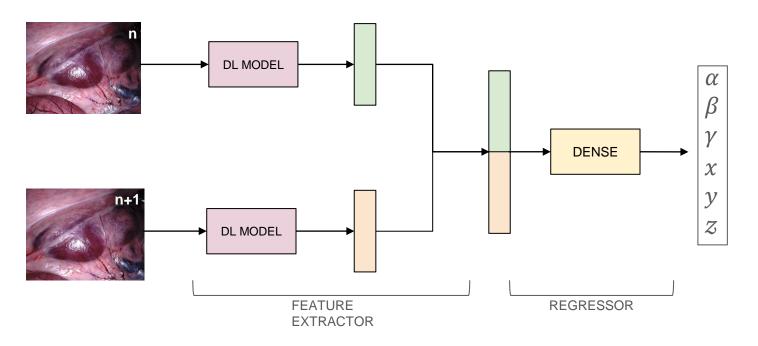
$$R = \begin{bmatrix} r11 & r12 & r13 \\ r21 & r22 & r23 \\ r31 & r32 & r33 \end{bmatrix}$$

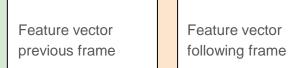
$$\beta = A \tan 2 \left(\pm \sqrt{r_{23}^2 + r_{33}^2}, r_{13} \right)$$

$$\alpha = A \tan 2 \left(\frac{r_{33}}{c \beta}, \frac{-r_{32}}{c \beta} \right)$$

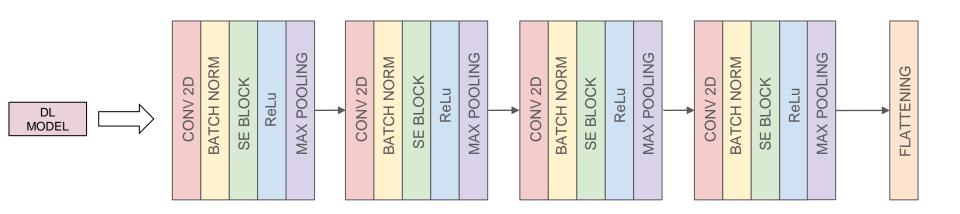
$$\gamma = A \tan 2 \left(\frac{r_{11}}{c \beta}, \frac{-r_{12}}{c \beta} \right)$$

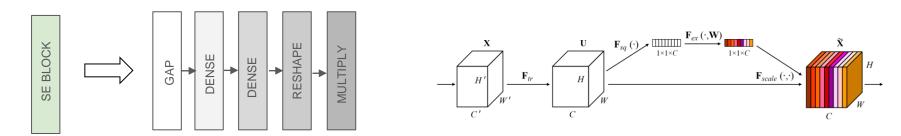
Two tails architecture





From scratch architecture



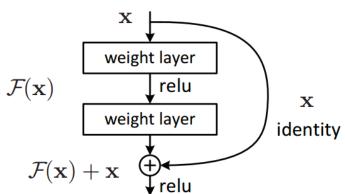


ResNet50 MODEL

- ResNet-50 introduced the concept of residual learning to address the challenge of training very deep neural networks and mitigating the vanishing gradient problem.
- A residual block contains a shortcut or skip connection that skips one or more layers, allowing the network to learn the residual (difference) between the input and output of those skipped layers.
- Weights were initialized to pre-trained model from image-net, but adjusted to fit our dataset during training

"Instead of figuring out the entire journey, let's figure out the changes we need to make at each step, and then just add those changes to the starting point."

- chat GPT et al.(2024)





Model training

FROM SCRATCH MODEL

- TRAINING VIDEOS : 3 (v2, v3, v4)
- NUM. TRAINIGN IMAGES: 1784
- TEST VIDEO: **1** (**v1**)
- LOSS FUNCTION : Mean Square Error (MSE)
- BATCH : **12**
- LEARNING RATE (LR) : **0.0001**
- CALLBACKS:
 - EARLY STOPPING PATIENCE : 12
 - REDUCE LR ON PLATEU FACTOR: 6
- NUM. PARAMETERS : 40 millions

RESNET50 MODEL

ResNet-50

224 + 224 HOB Image TRAINING VIDEOS: 3 (v2, v3, v4)

- NUM. TRAINIGN IMAGES: 1784

- TEST VIDEO: **1** (**v1**)

- BATCH : **4**

- LEARNING RATE (LR) : **0.0001**

- CALLBACKS:

- EARLY STOPPING PATIENCE : 10

- REDUCE LR ON PLATEU FACTOR : 3

- LOSS FUNCTION : Mean Square Error (MSE)

- NUM. PARAMETERS : **340 millions**

1xt conv, 64
3x2 conv, 64
1xt conv, 54
1xt conv, 54
3x3 conv, 64
3x3 conv, 64
1xt conv, 56
1xt conv, 56
1xt conv, 54

1x1 conv, 128 3x3 conv, 128 1x1 conv, 512 1x1 conv, 512

1x1 conv, 256/2 1x1 conv, 256/2 3x3 conv, 256 1x1 conv, 1024

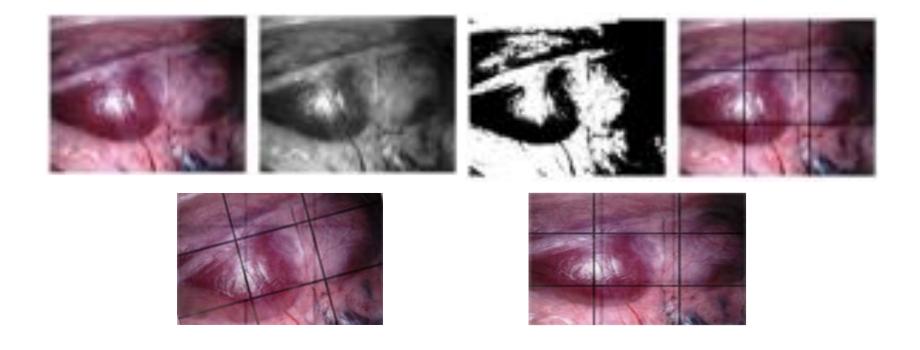






7x7 avg pool

Image preprocessing



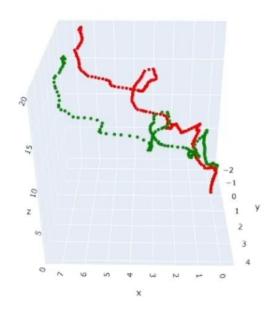
- RGB image \rightarrow (m, 512, 640, 3) \rightarrow 983,040 data points per image
- Binary image \rightarrow (m, 512, 640, 1) \rightarrow 327,680 data points per image

Effects of preprocessing

	Т	ranslation error	Rotation error
Base line			
Grayscale		•	•
Binary	J	•	•
Grid		•	•

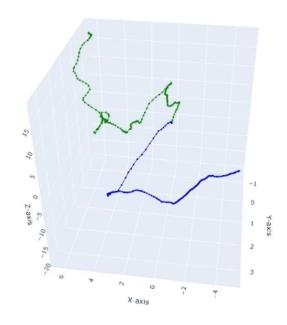
FINAL RESULTS

FROM SCRATCH MODEL



FROM SCRATCH MODEL VS TARGET TRAJECTORY

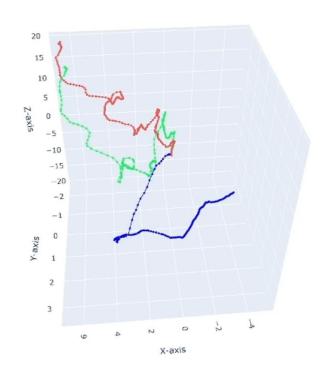
RESNET50 MODEL

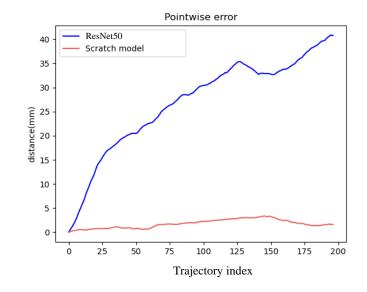


RESNET 50 VS TARGET TRAJECTORY

RESULTS COMPARISON

FROM SCRATCH MODEL VS RESNET 50 VS TARGET TRAJECTORY





NUMERICAL METRICS

	Scratch model	Resnet50
Mean Angular Error (degree)	10.7	12.4
Euclidian Distance (mm)	1.7	26.9

CONCLUSION

Limitation

- Texture-less tissues and Lambertian Reflection
- GPUs limitation
- Computationally intensive
- Overfitting

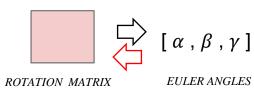
Future work

- Structural similarity
- Larger sequential
- Non sub-sequence frames
- Pretrained model on endoscopic camera dataset
- Ensembled light weight models

THANK YOU FOR YOUR ATTENTION

QUESTIONS?

DIRECT PROBLEM



R: rotation matrix

$$R_{x,y',z''}(a,\beta,\gamma) = R_x * R_{y'} * R_{z''}$$

$$R_x = \begin{bmatrix} 1 & 0 & 0 \\ 0 & ca & -sa \\ 0 & sa & ca \end{bmatrix}$$

$$R_{y\prime} = \begin{bmatrix} c\boldsymbol{\beta} & 0 & s\boldsymbol{\beta} \\ 0 & 1 & 0 \\ -s\boldsymbol{\beta} & 0 & c\boldsymbol{\beta} \end{bmatrix}$$

$$R_{z''} = \begin{bmatrix} c\gamma & -s\gamma & 0 \\ s\gamma & c\gamma & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

$$R_{x,y',z''}(a,\beta,\gamma) = \begin{bmatrix} 1 & 0 & 0 \\ 0 & ca & -sa \\ 0 & sa & ca \end{bmatrix} * \begin{bmatrix} c\beta & 0 & s\beta \\ 0 & 1 & 0 \\ -s\beta & 0 & c\beta \end{bmatrix} * \begin{bmatrix} c\gamma & -s\gamma & 0 \\ s\gamma & c\gamma & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

$$R_{x,y',z''}(a,\beta,\gamma) = \begin{bmatrix} c\beta & 0 & s\beta \\ sas\beta & ca & -sac\beta \\ -s\beta ca & sa & cac\beta \end{bmatrix} * \begin{bmatrix} c\gamma & -s\gamma & 0 \\ s\gamma & c\gamma & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

$$R_{x,y',z''}(a,\beta,\gamma) = \begin{bmatrix} c\beta c\gamma & -c\beta s\gamma & s\beta \\ sas\beta c\gamma + cas\gamma & -sas\beta s\gamma + cac\gamma & -sac\beta \\ -s\beta cac\gamma + sas\gamma & s\beta cas\gamma + sac\gamma & cac\beta \end{bmatrix}$$