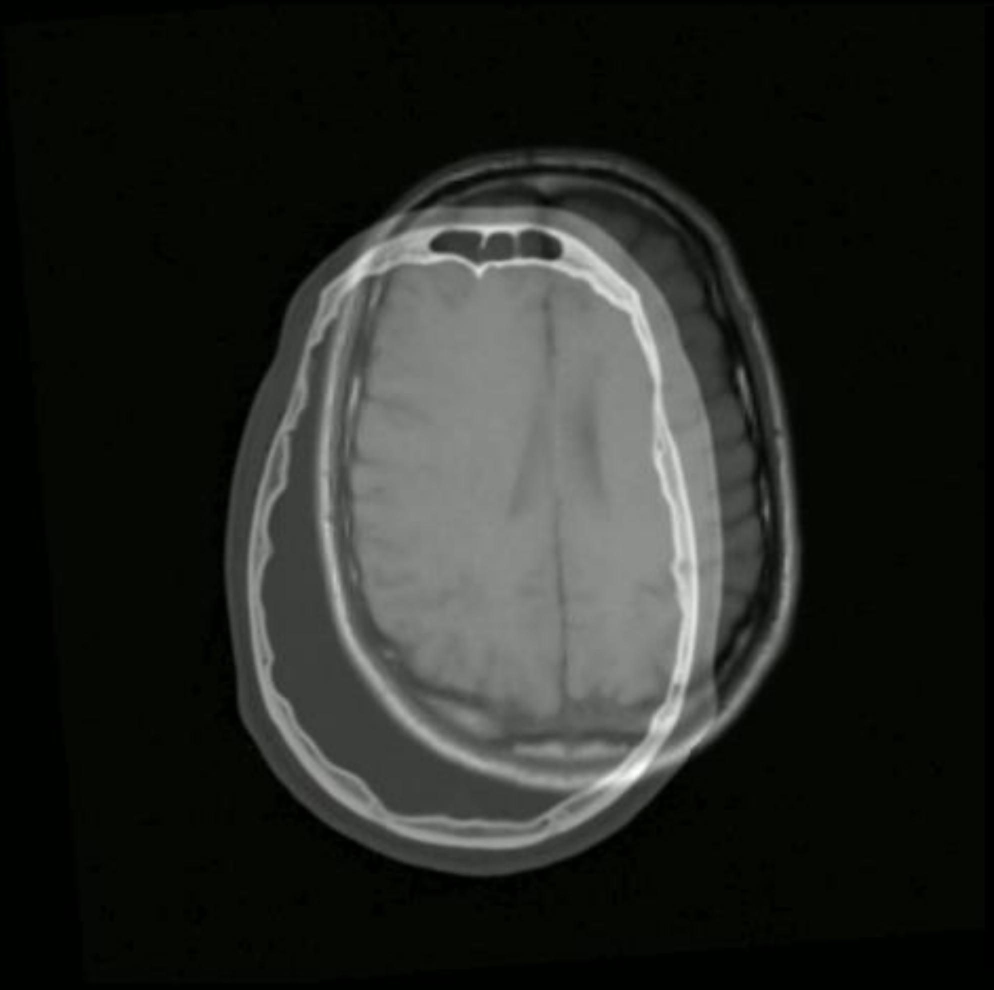
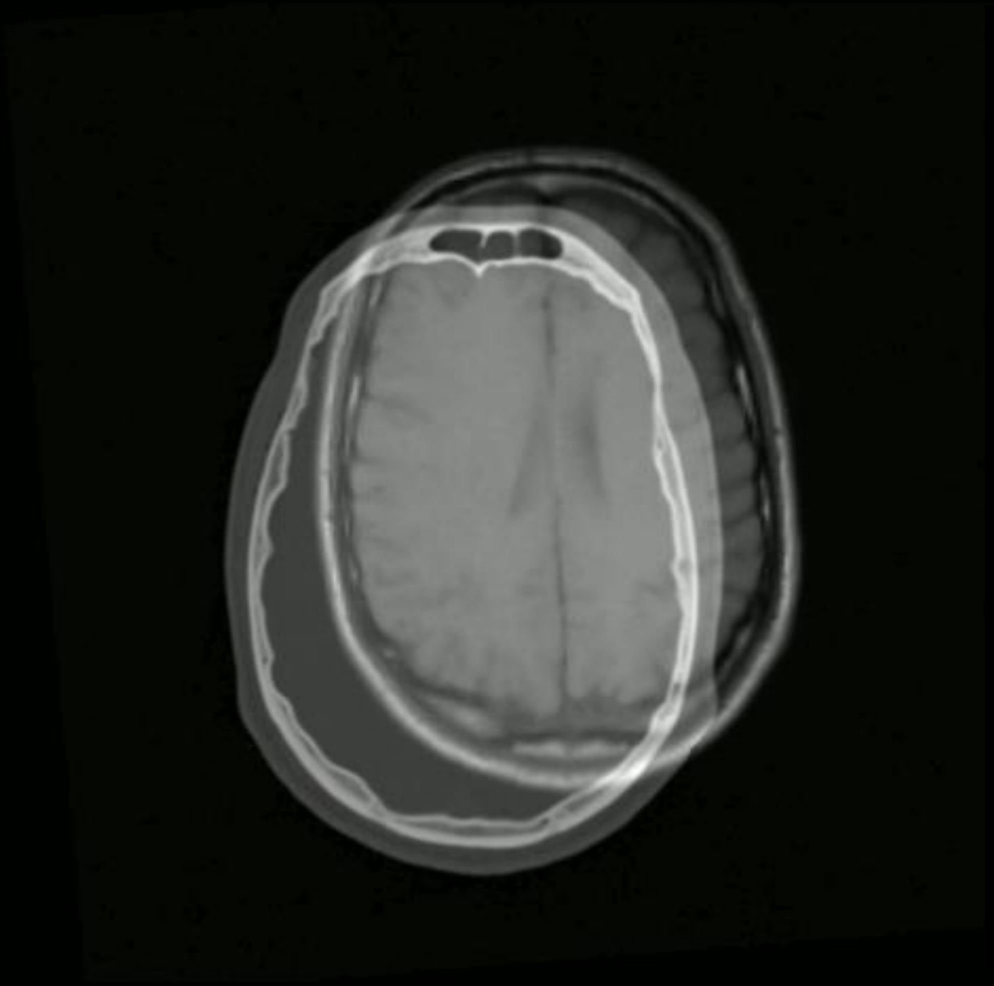
IMAGE ALIGNMENT WITH AND WITHOUT LABELED MASK

Presented By: Neha Goyal

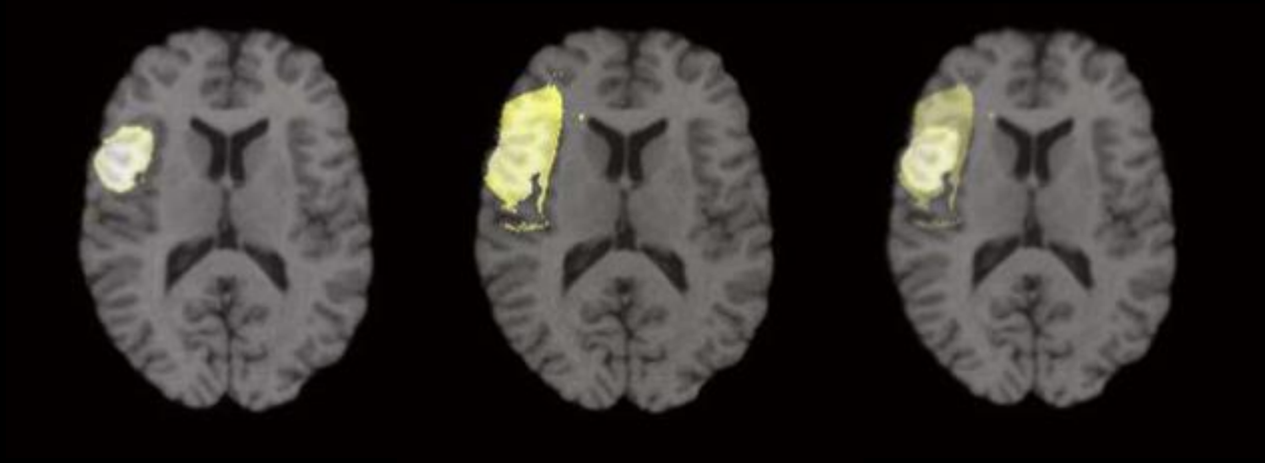


What is Image Registration?



What type of images can be used?

Multi-temporal analysis

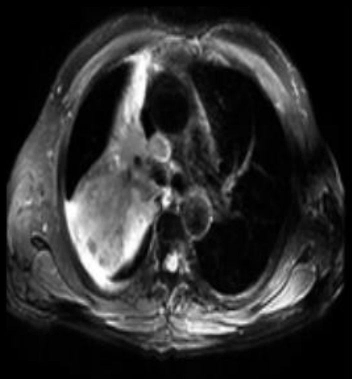


Brain scan image

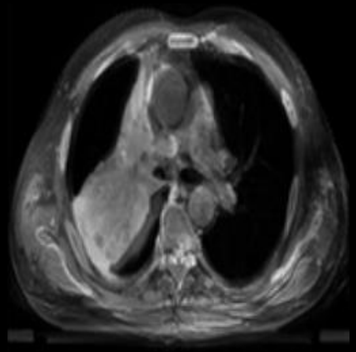
Brain scan image acquired after 30 days

Warped image

CT



MRI



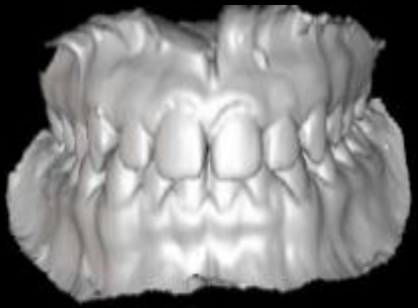
Warped image

Multi-modal analysis

Multi–view analysis

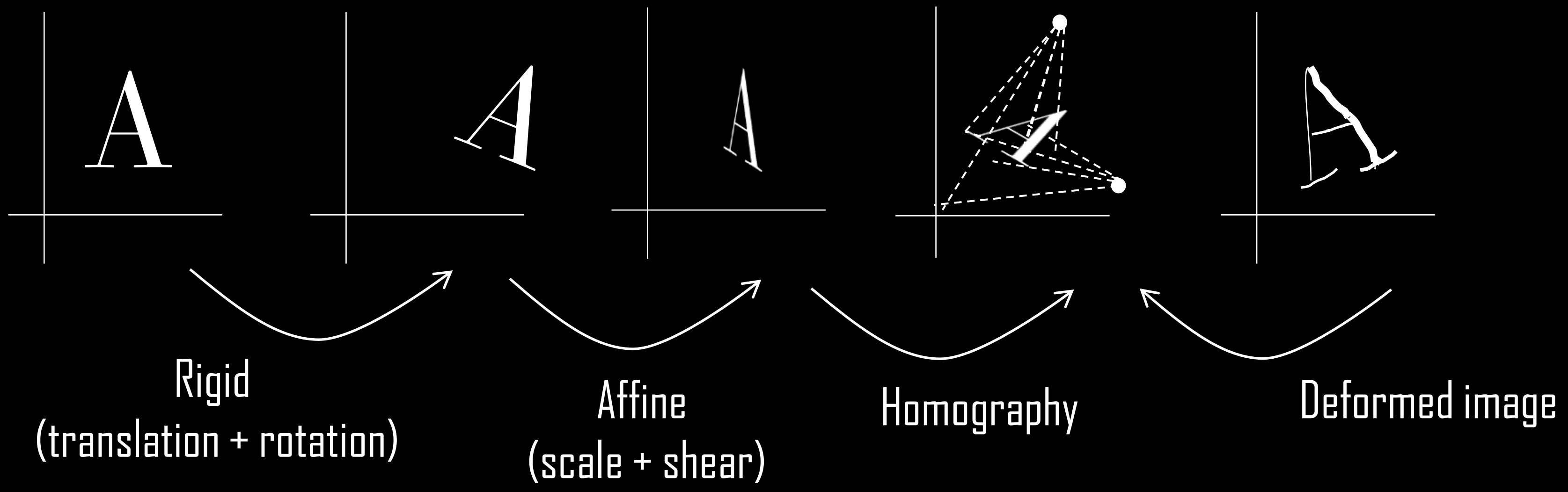
3D denture

2D



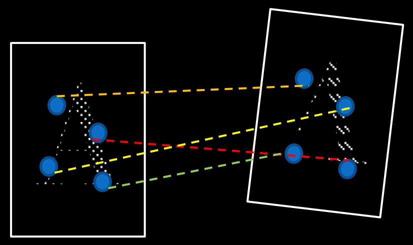
Warped image

Different transformation matrix :



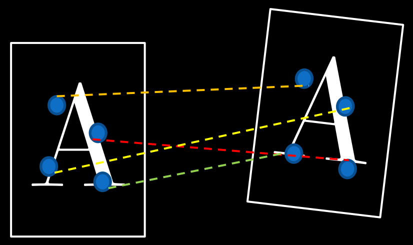
Different registration method:

- Intensity based methods



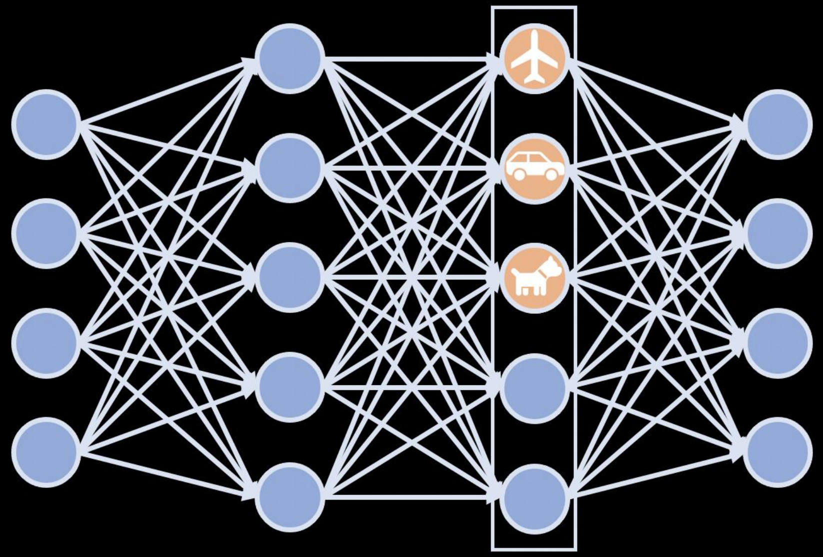
Different registration method:

- Intensity based methods
- Feature matching method



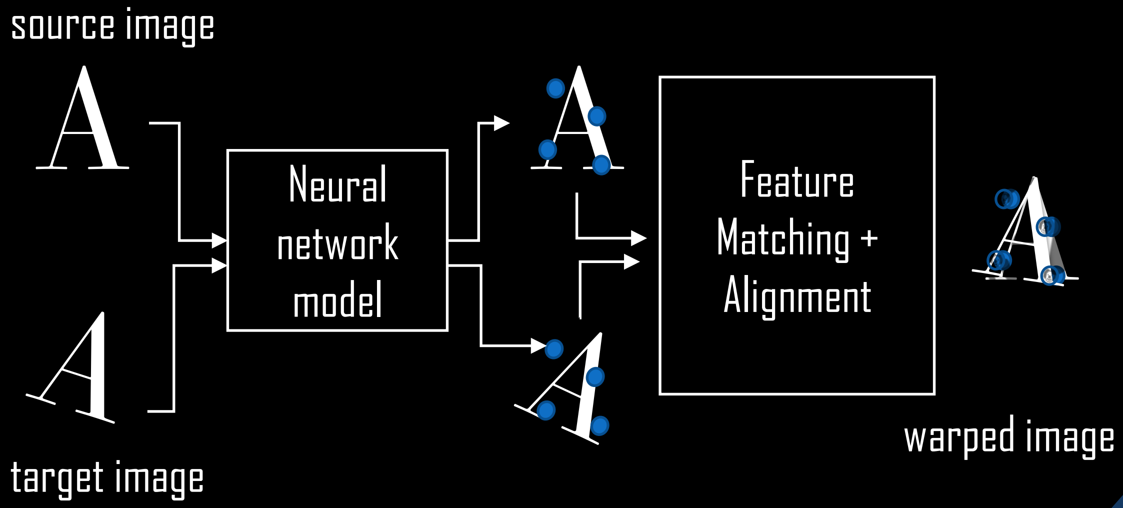
Different registration method:

- Intensity based methods
- Feature matching method
- Deep learning method



Different registration method:

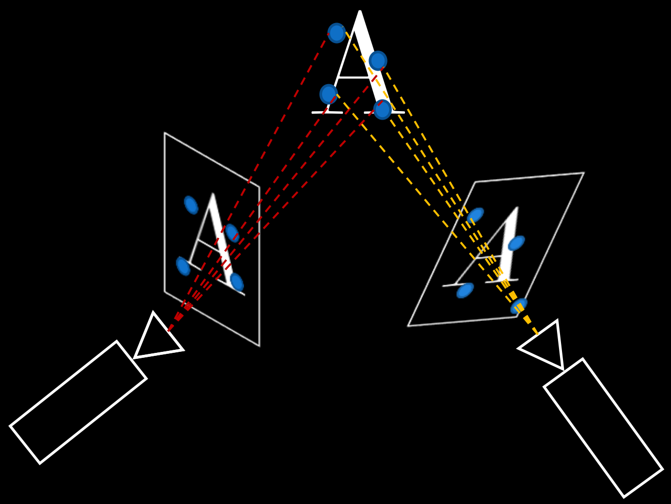
- Intensity based methods
- Feature matching method
- Deep learning method
  - *Feature matching based deep learning*



Different registration method:

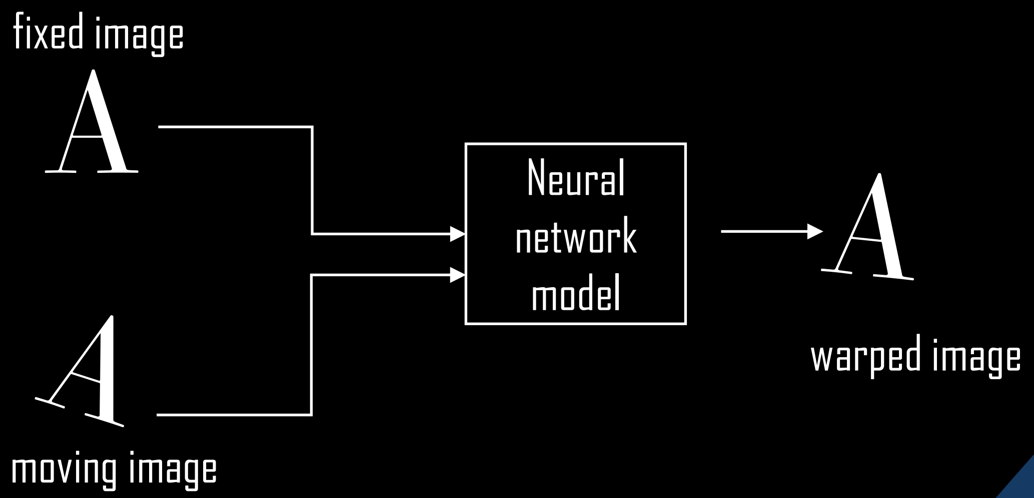
- Intensity based methods
- Feature matching method
- Deep learning method
    - *Feature matching based deep learning*
    - *Homography learning*

One to one mapping with homography matrix



Different registration method:

- Intensity based methods
- Feature matching method
- Deep learning method
    - *Feature matching based deep learning*
    - *Homography learning*
    - *Reinforcement learning*

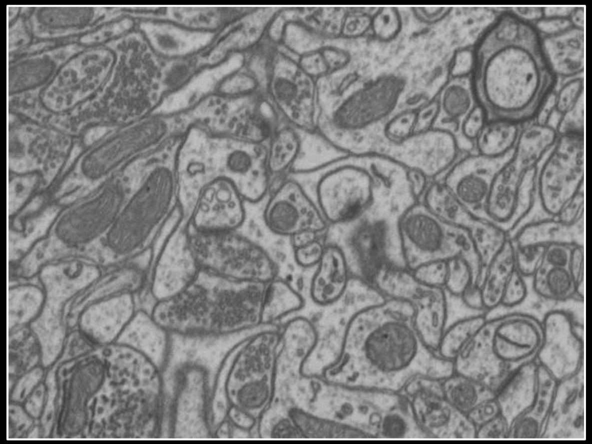


In this thesis research two different registration methods are used

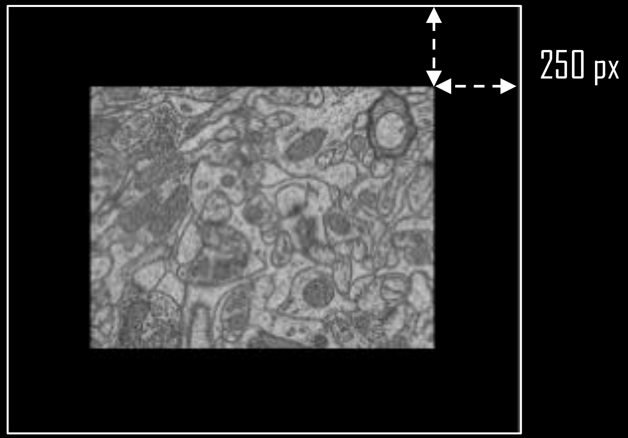
- Feature matching method
- Monai, deep learning framework

Datasets:

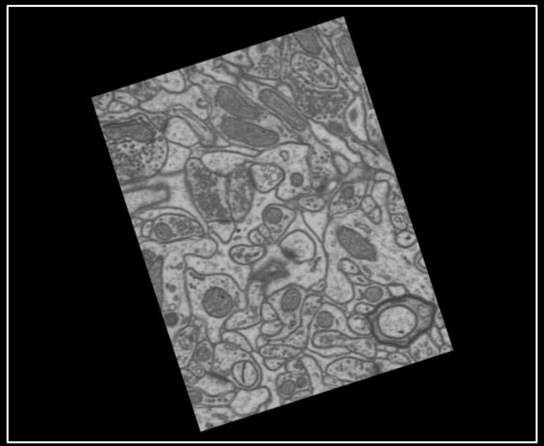
- Electron microscopy 2D image dataset with labelled mask data as mitochondria mask , called Lucchi++



Lucchi++ image



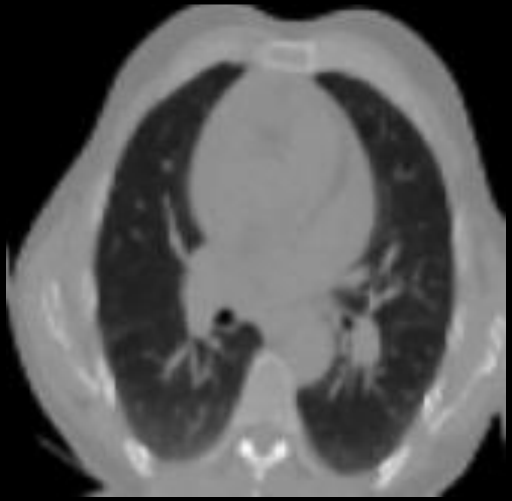
Padding is added



input image for feature matching

Datasets:

- CT images acquired at different time points for a single patient
- Intrasubject 3D high-resolution CT inhale/exhale thorax images



3D image capture when subject inhaling

3D image capture when subject exhaling

Alignment with feature matching

OpenCV

Feature Detection | Keypoints

Feature Description

Feature Matching

Transformation Matrix

Alignment with feature matching

OpenCV

Feature Detection → Keypoints

↓

Feature Description → Keypoint descriptors

Feature Matching

Transformation Matrix

Feature detection and description

- SIFT
- FAST
- ORB
- BRISK
- FREAK

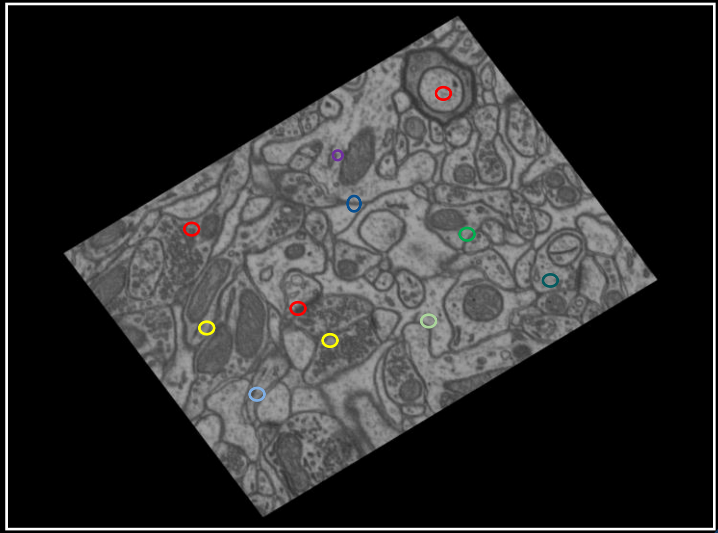


image with keypoints

Feature detection and description

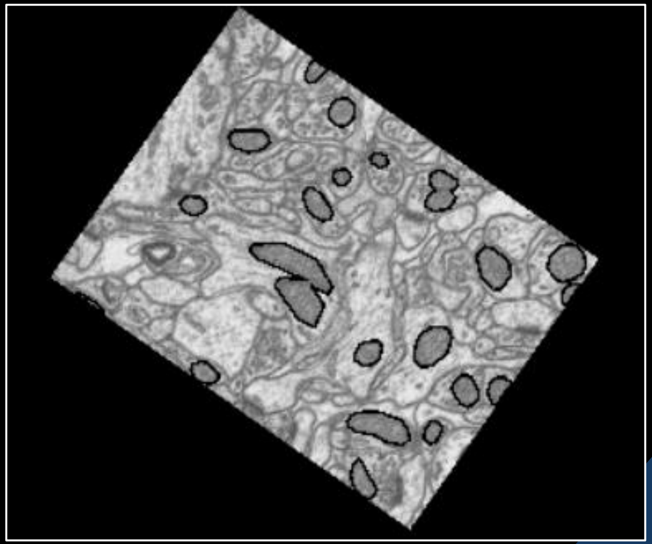
- SIFT
- FAST
- BRISK
- FREAK
- ORB
- MITO features (Ours)

MITO feature detection

- Mito mask of each image was used to find bounding box or contours
- Each contour is used to calculated approx. polygon that is drawn on the image
- Each polygon has list of (x, y) values that are considered as keypoint coordinates

mask image

image with contour

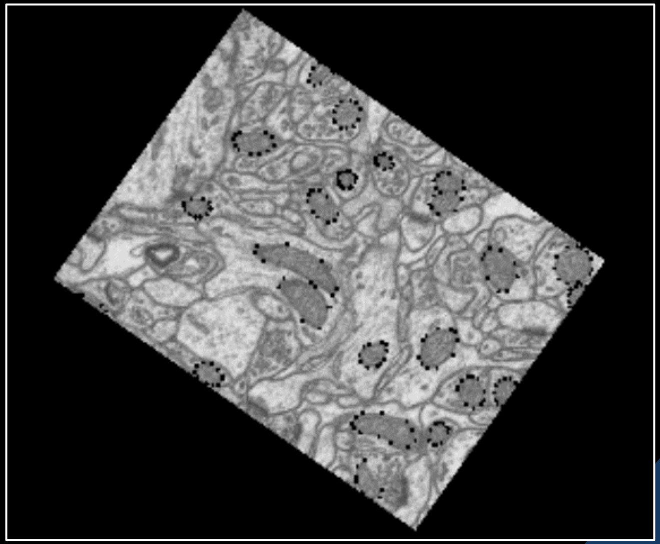


MITO feature detection

- Mito mask of each image was used to find contours
- Each contour is used to calculated approx. polygon that is drawn on the image
- Each polygon has list of (x, y) values that are considered as keypoint coordinates

mask image

image with keypoints



Alignment with feature matching

OpenCV

Feature Detection → Keypoints

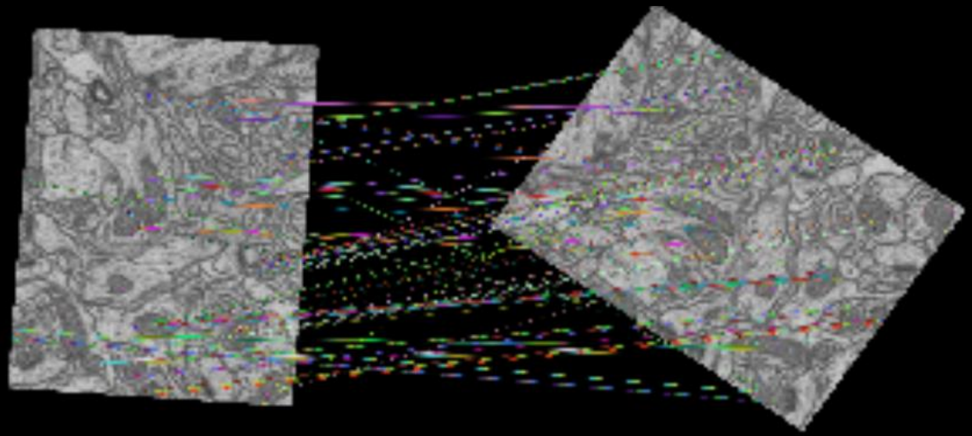
Feature Description → Keypoint descriptors

Feature Matching → Best matched Keypoints

Transformation Matrix

Feature Matching

- Brute Force (BF)
- Fast Library for Approximate Nearest Neighbors (FLANN)



Alignment with feature matching

OpenCV

Feature Detection	Keypoints
Feature Description	Keypoint descriptors
Feature Matching	Best matched Keypoints
Transformation Matrix	Warp source image to target using this matrix

Experiments with feature matching

Detector	Descriptor	Matcher	Matrix	MITO
SIFT	SIFT	BF	AFFINE	True/False
		FLANN	AFFINE	True/False
SIFT	SIFT	BF	HOMOGRAPHY	True/False
		FLANN	HOMOGRAPHY	True/False

Detector	Descriptor	Matcher	Matrix	MITO
BRISK	BRISK	BF	HOMOGRAPHY	True/False
		FLANN		True/False
ORB	ORB	BF	HOMOGRAPHY	True/False
		FLANN		True/False
FAST	BRISK	BF	HOMOGRAPHY	True/False
		FLANN		True/False
ORB	BRISK	BF	HOMOGRAPHY	True/False
		FLANN		True/False
FAST	FREAK	BF	HOMOGRAPHY	True/False
		FLANN		True/False
ORB	FREAK	BF	HOMOGRAPHY	True/False
		FLANN		True/False

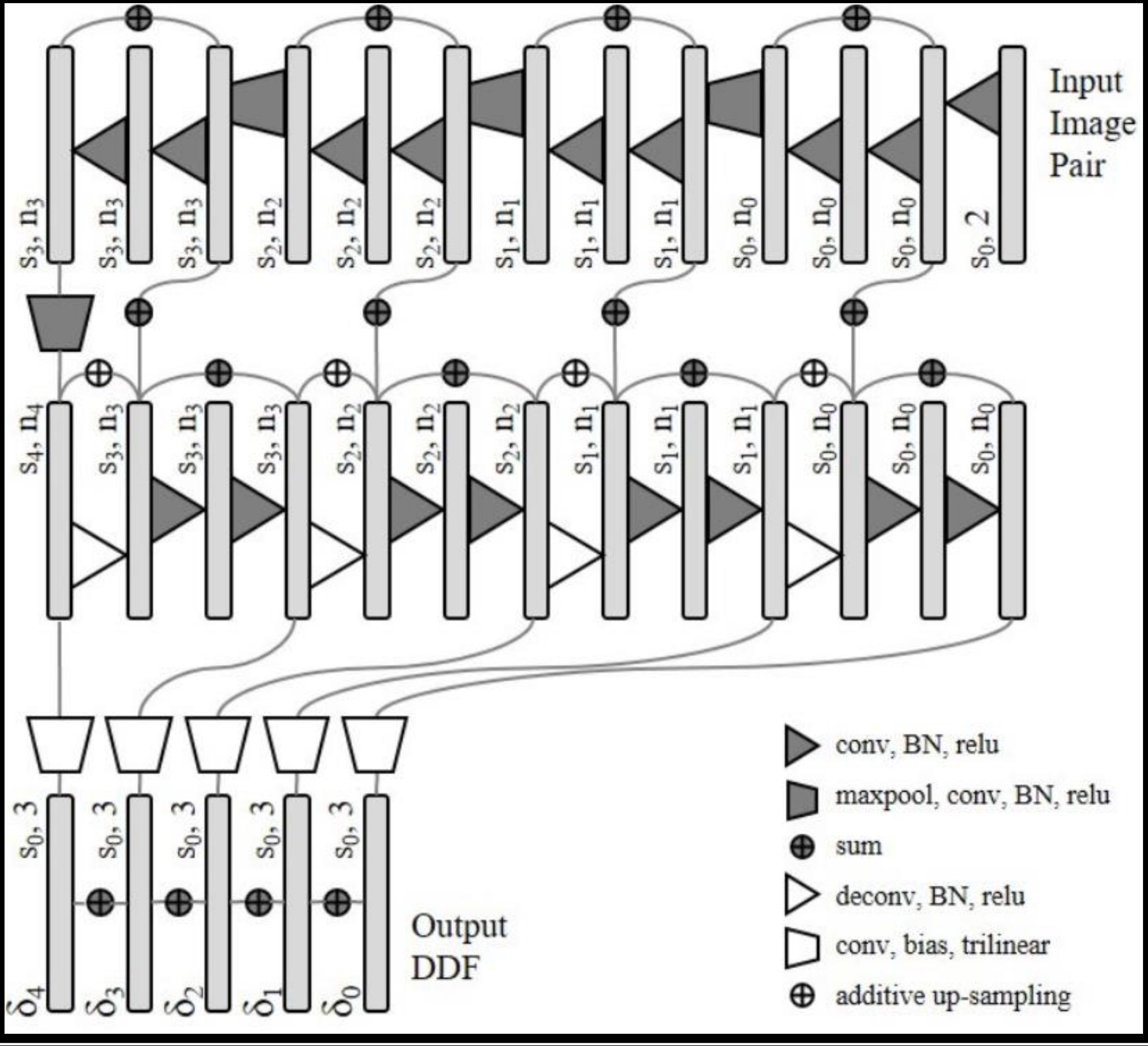
Experiments with feature matching

Detector	Descriptor	Matcher	Matrix
MITO	BRISK	BF	HOMOGRAPHY
		FLANN	
MITO	FREAK	BF	HOMOGRAPHY
		FLANN	

MONAI

- LocalNet method
- 3D Convolutional neural network
- Network architecture has encoder-decoder

MONAI



- Several types of shortcut layers, resnet, summation skip layers, additive trilinear upsampling
- Additive output layers to output a single DDF

For more detailed information : https://github.com/YipengHu/label-reg/tree/3fe086f8bb9d029acf9fdecba3cee92009cfb3dc

Image Unsupervised Registration

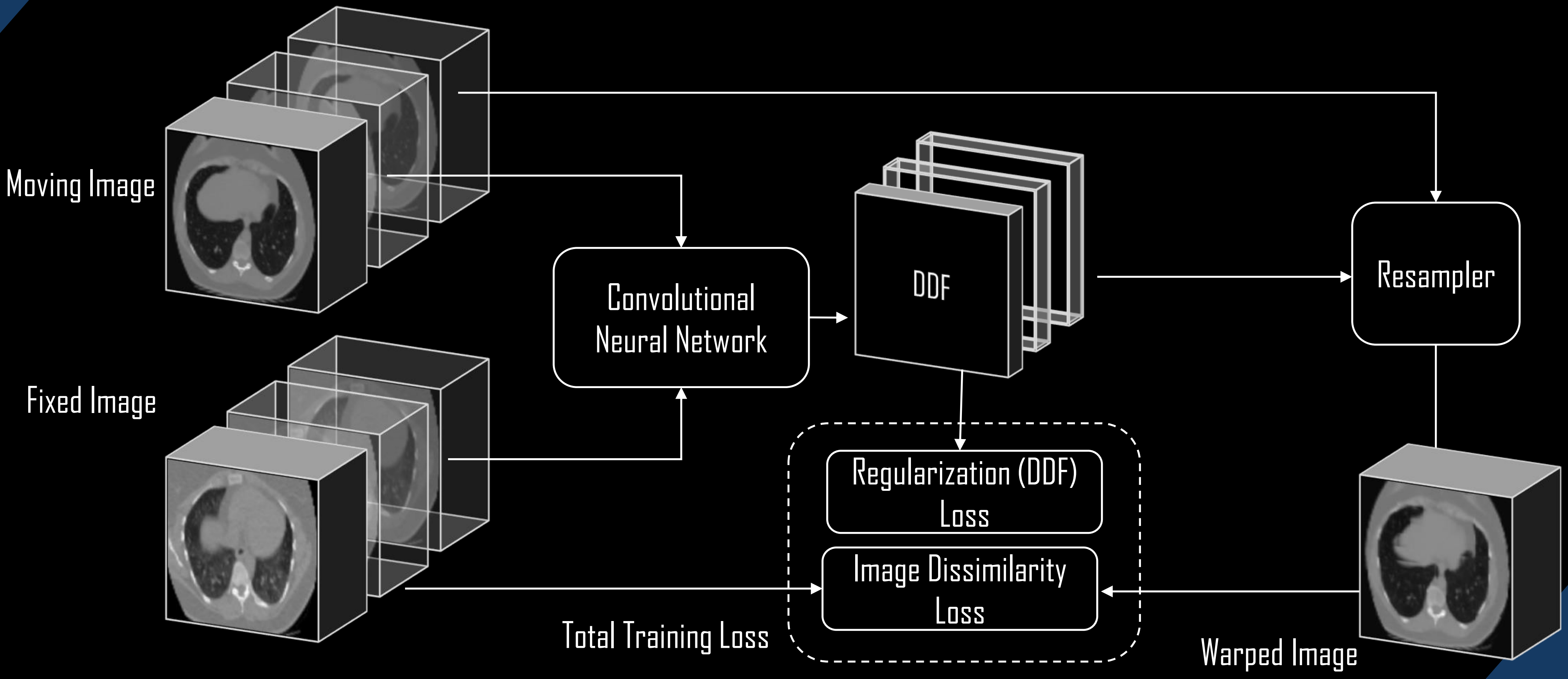
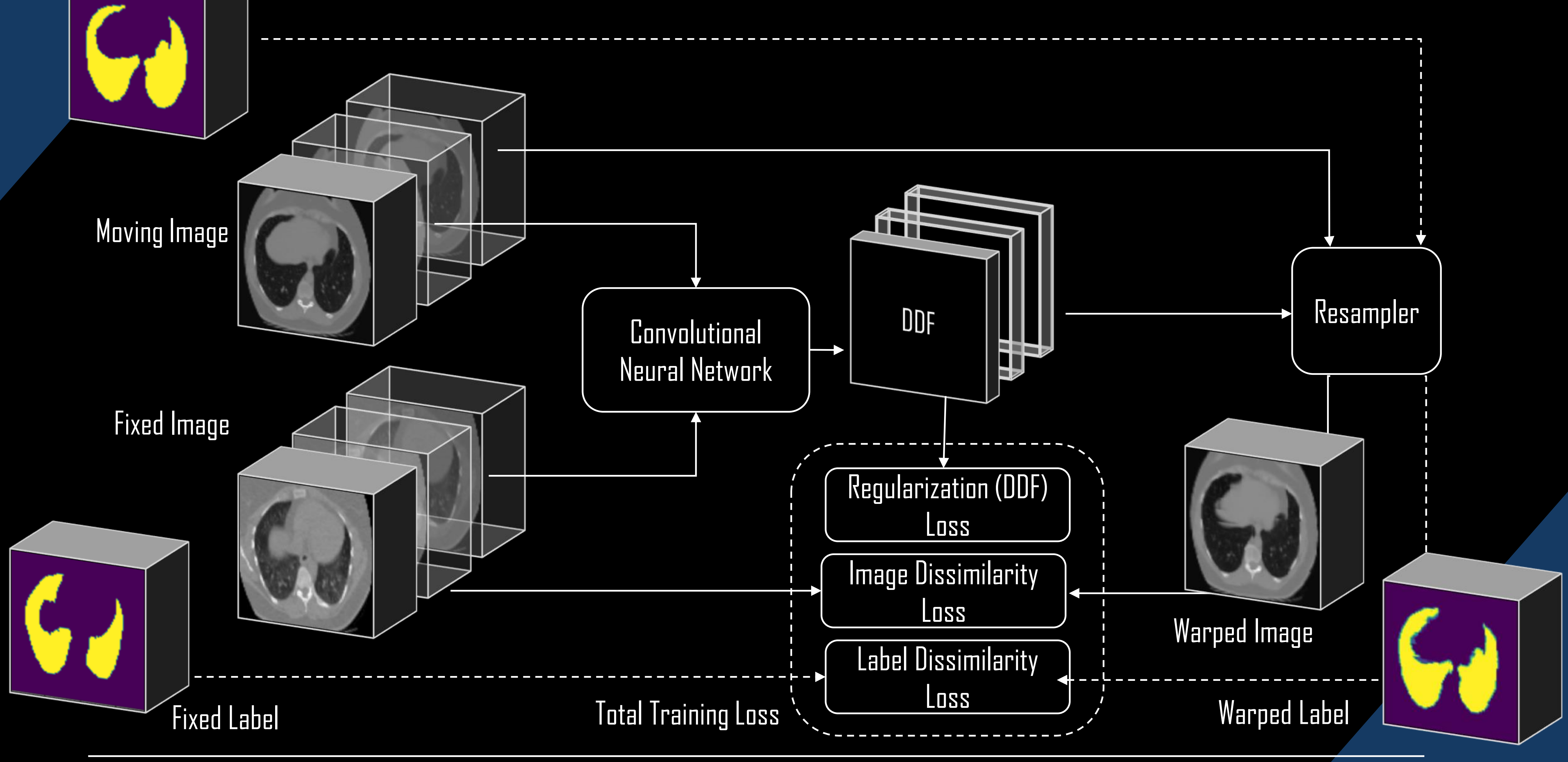
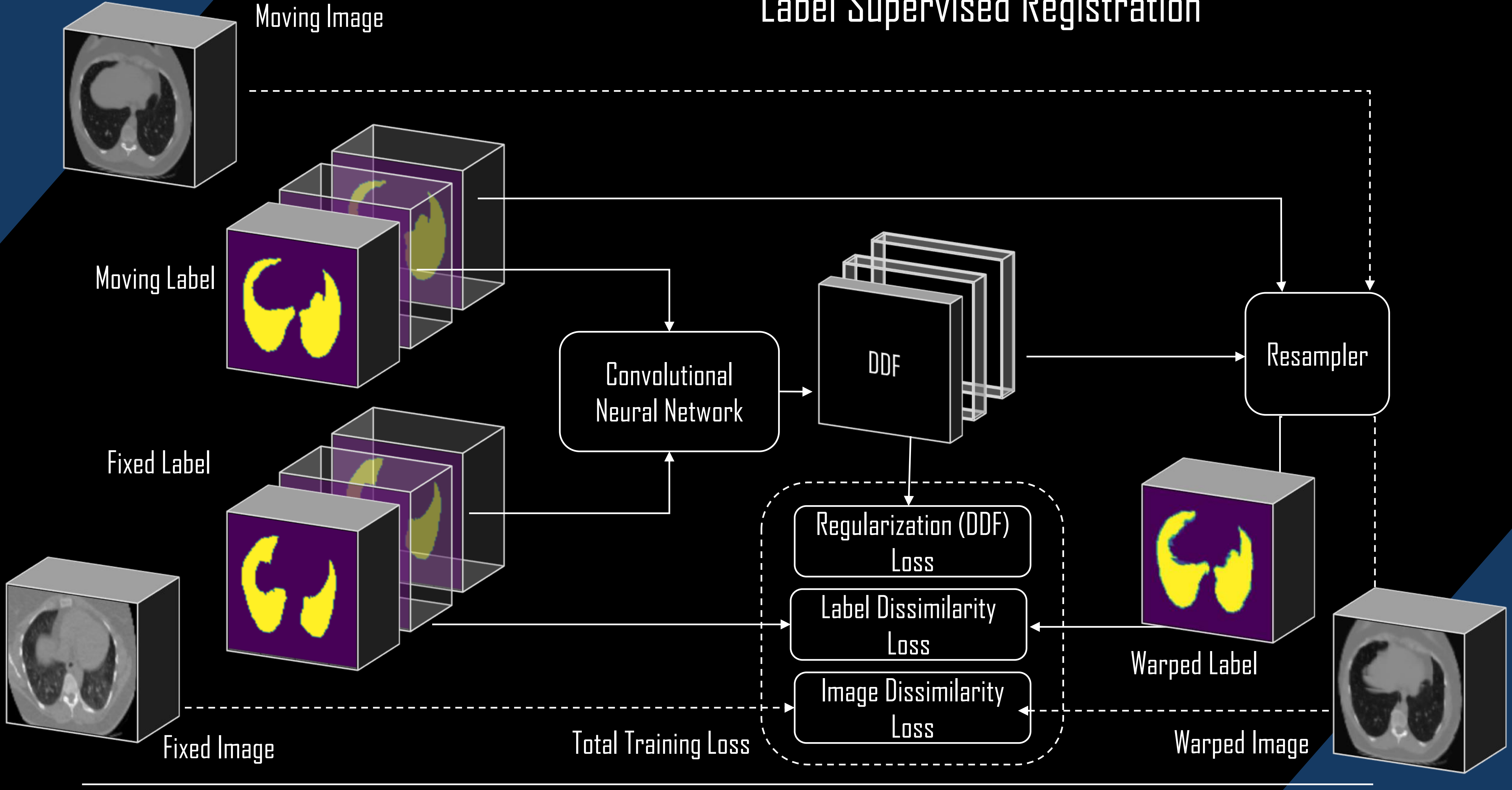


Image Supervised Registration

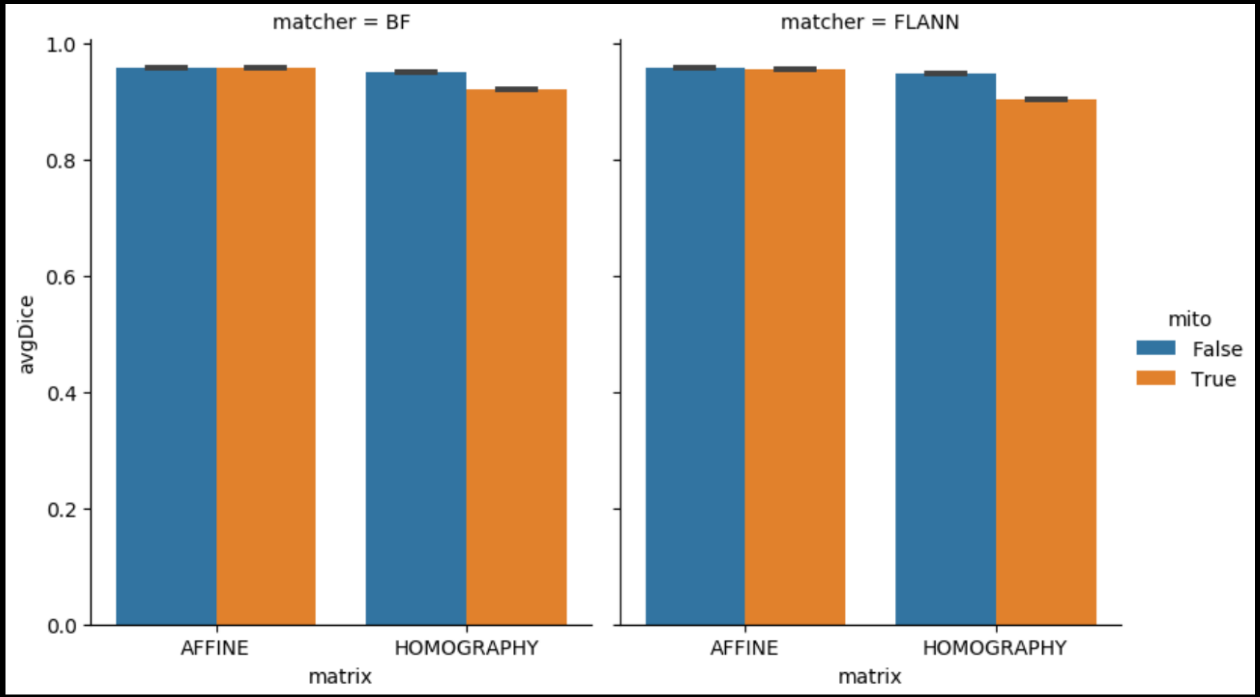


Label Supervised Registration



RESULTS

Image Alignment with SIFT



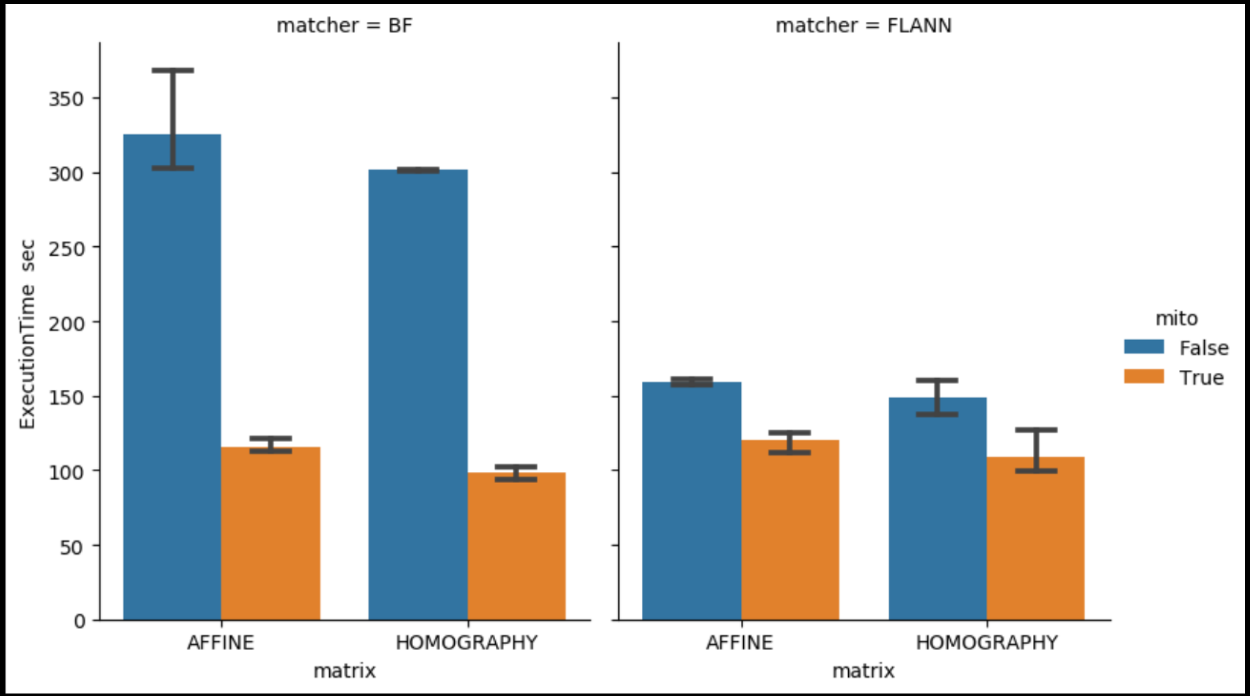
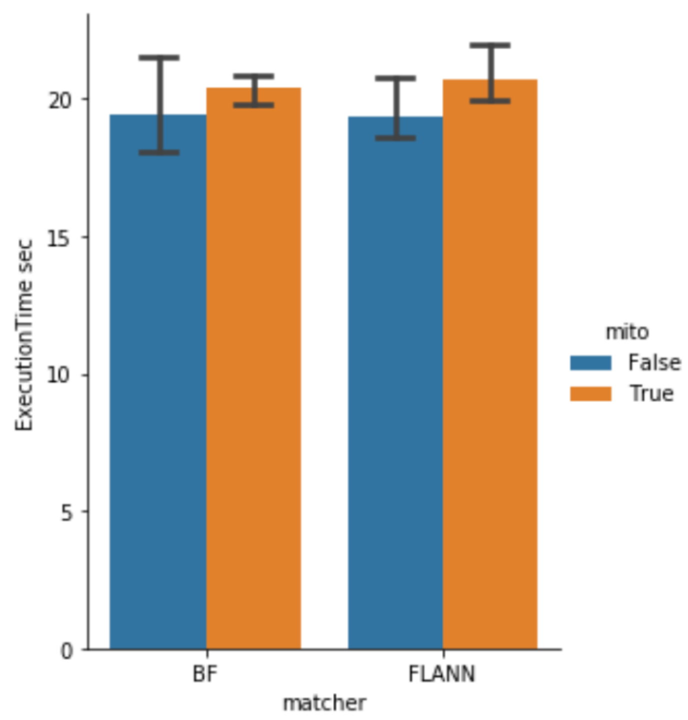
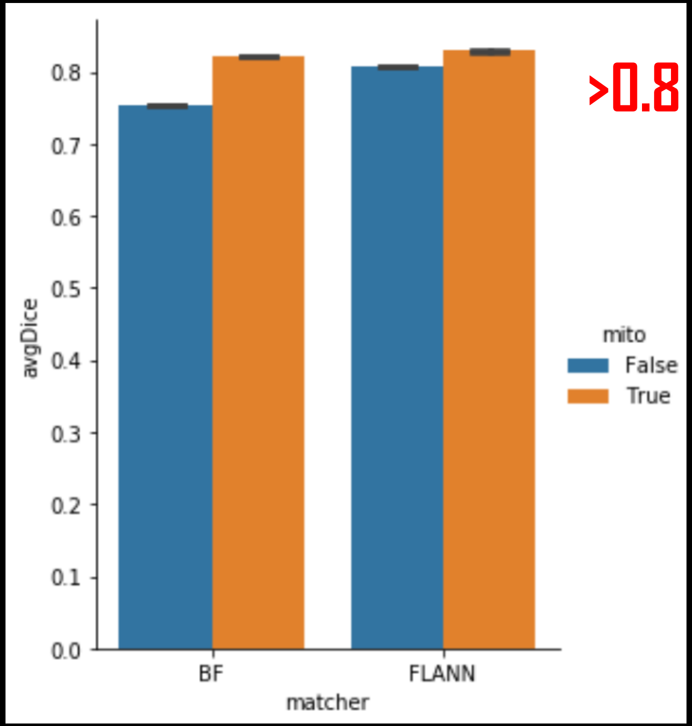


Image Alignment with ORB





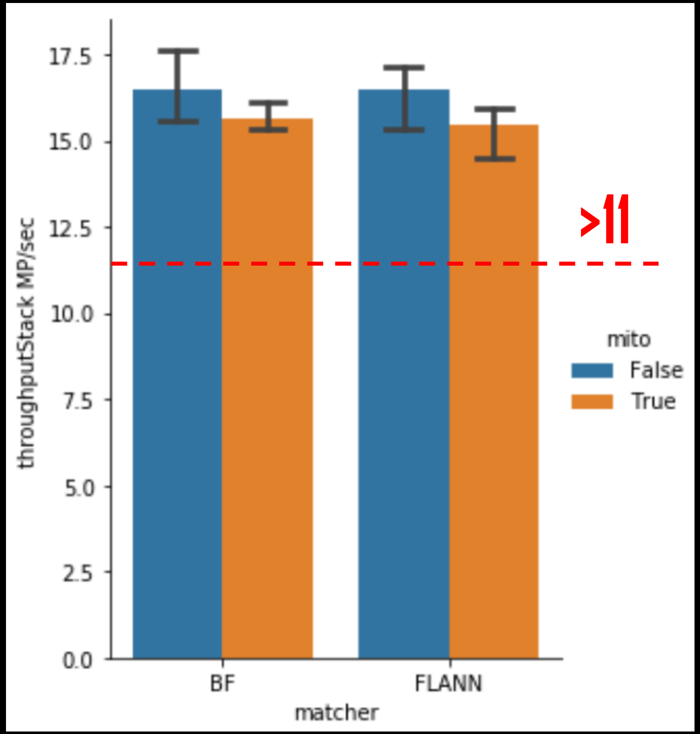
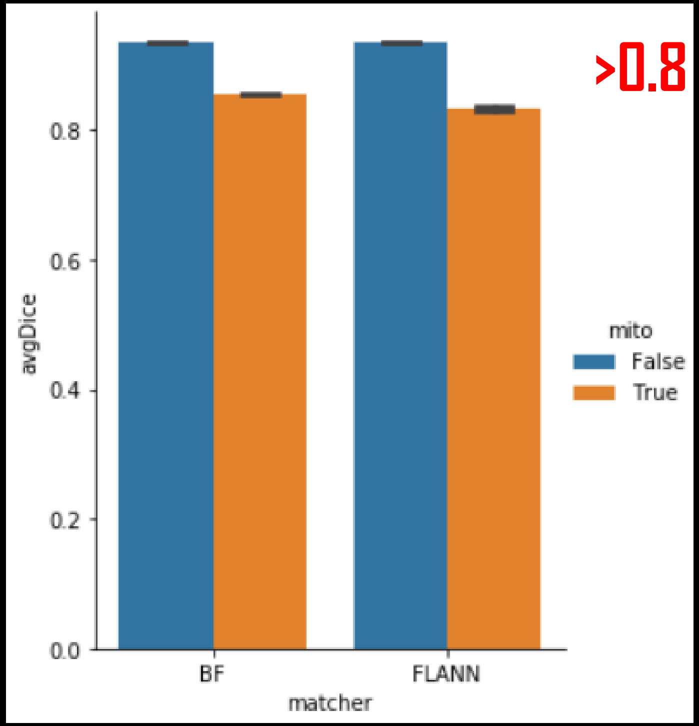
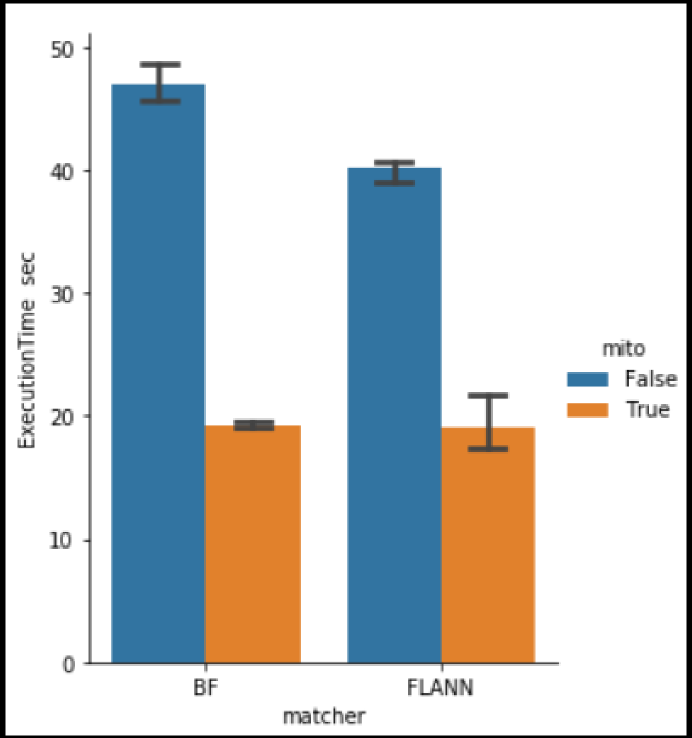


Image Alignment with BRISK





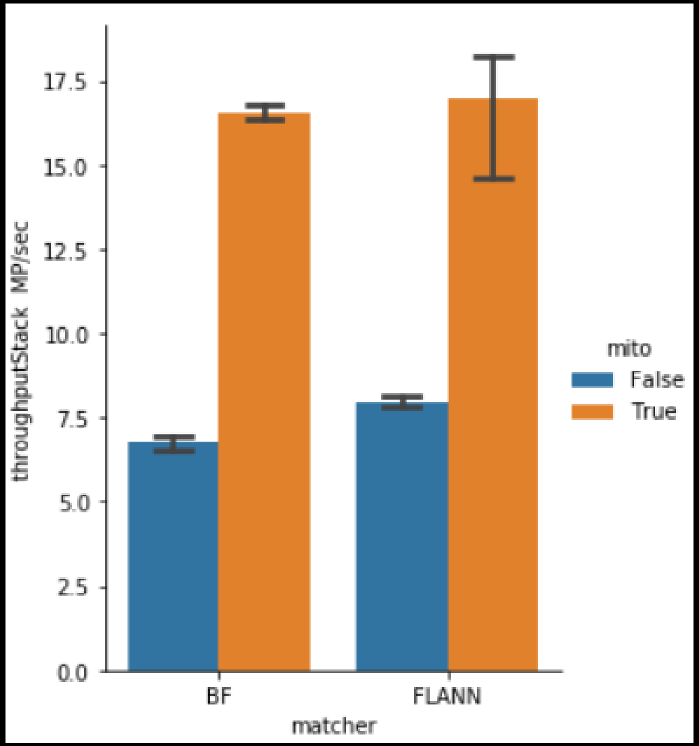
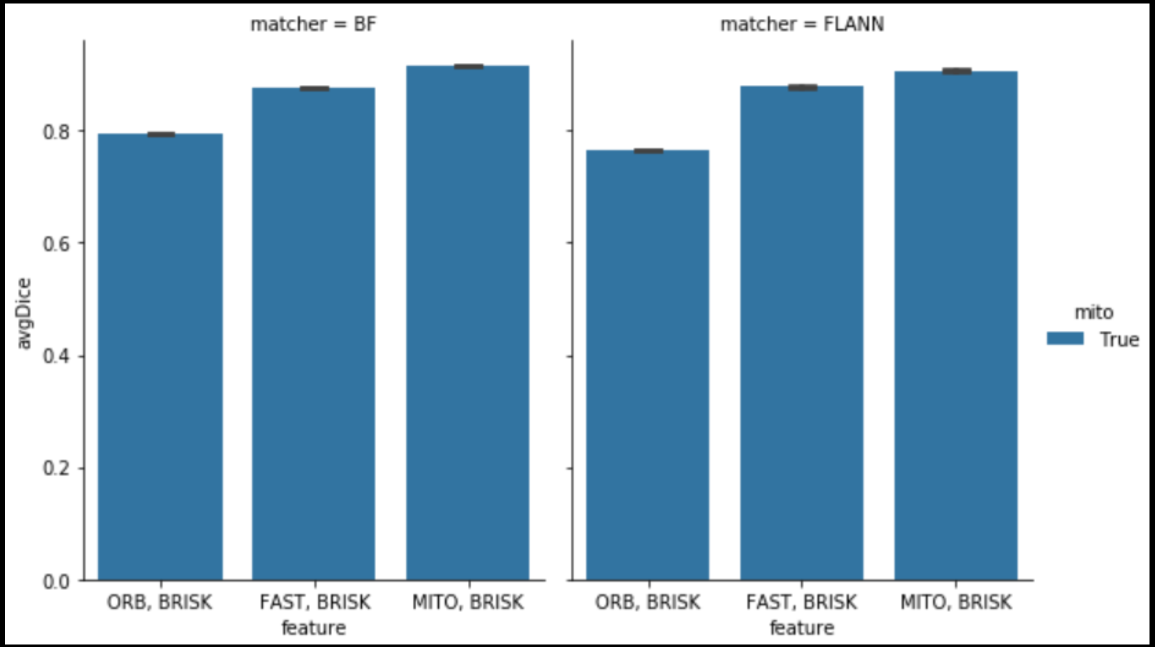
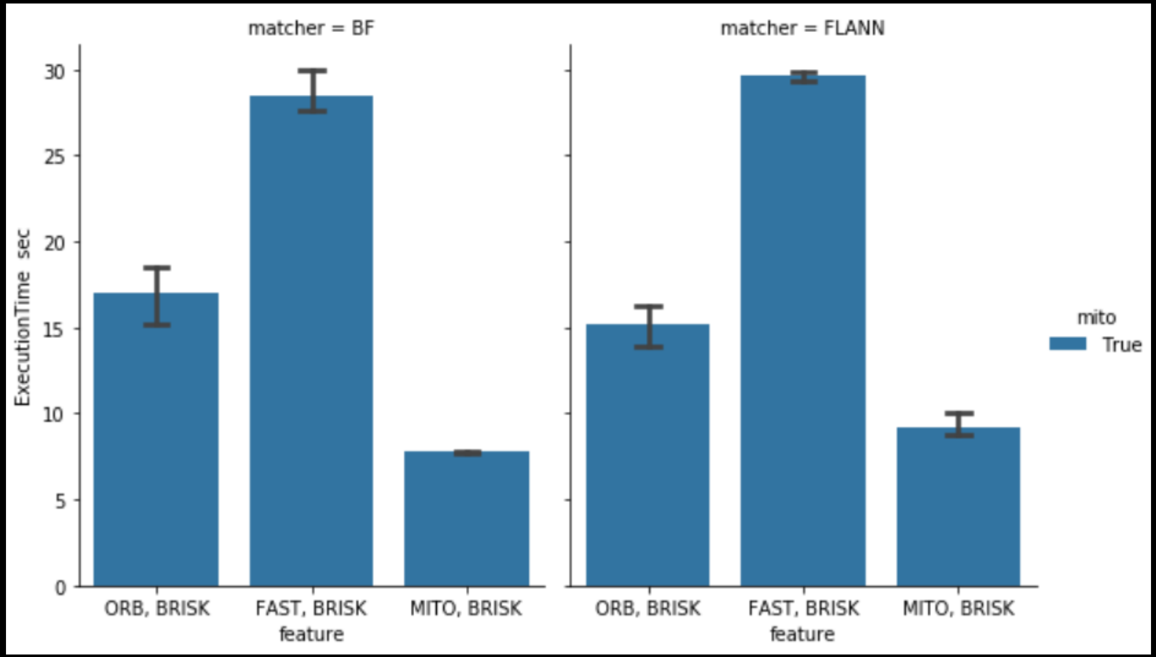


Image Alignment Comparison with MITO





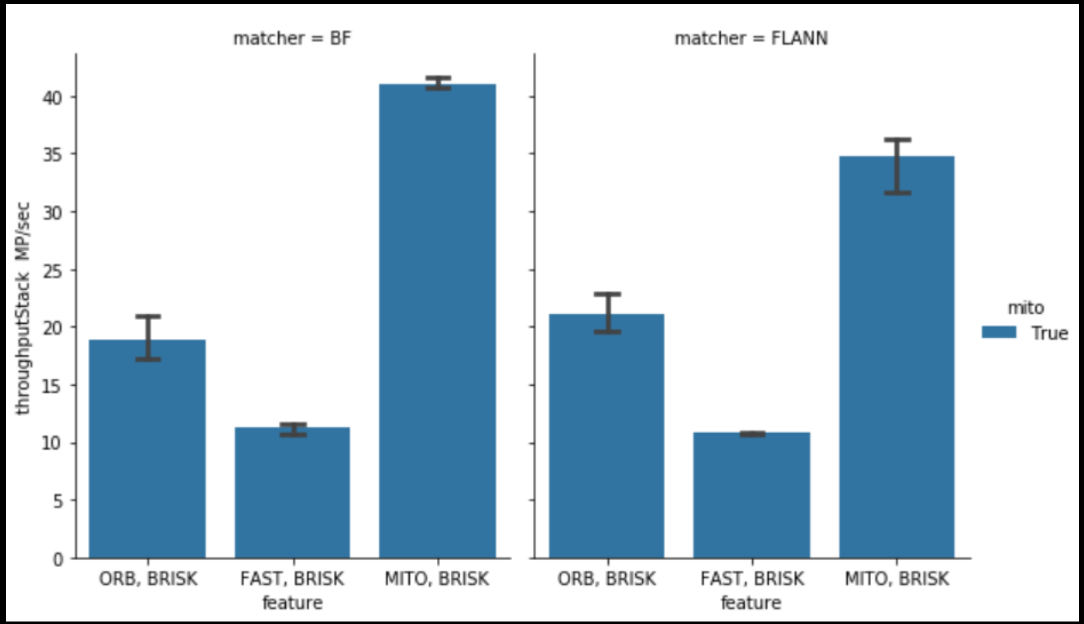
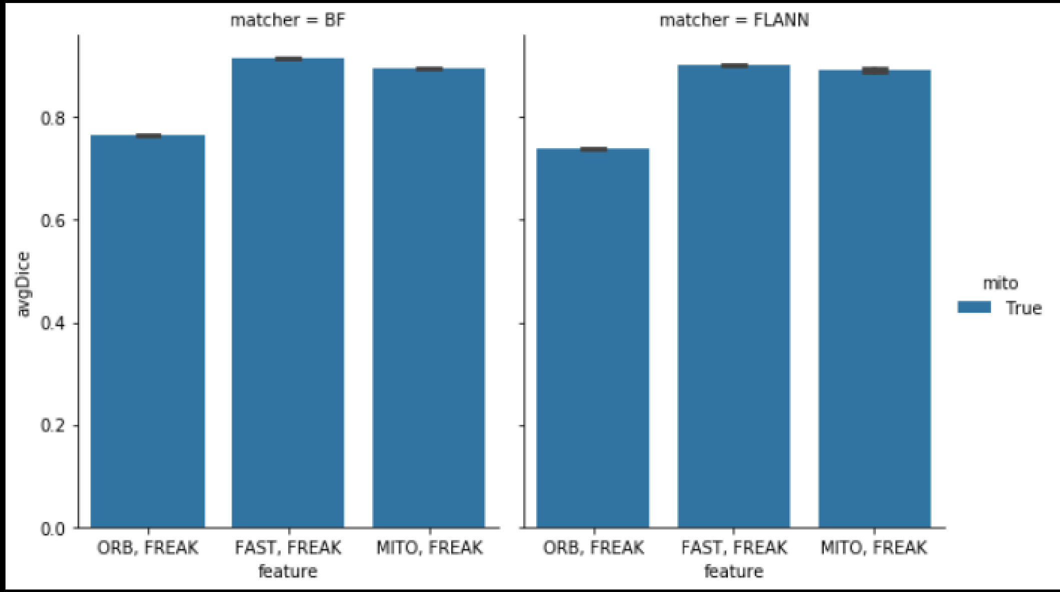
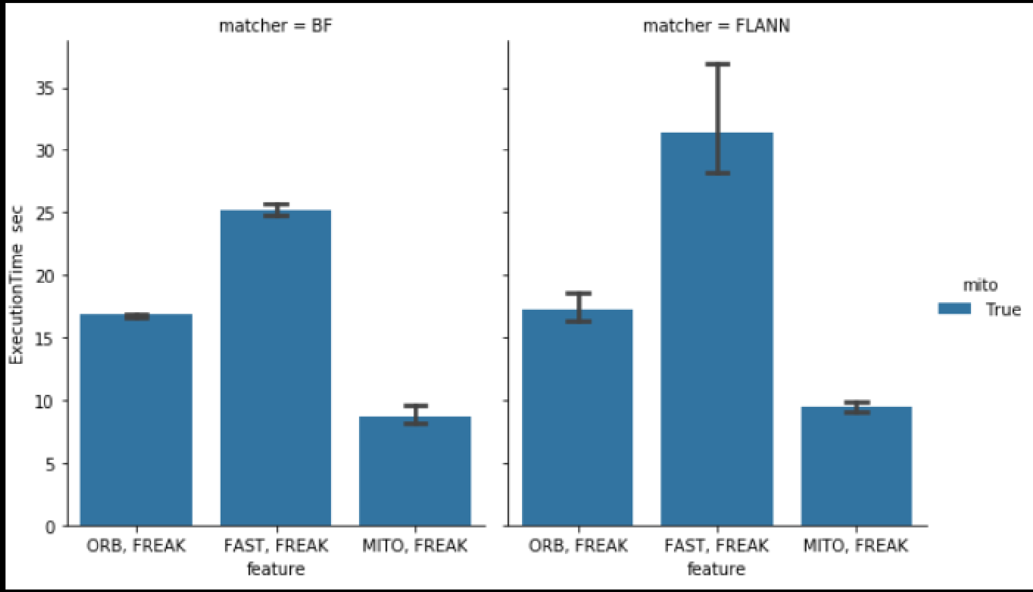
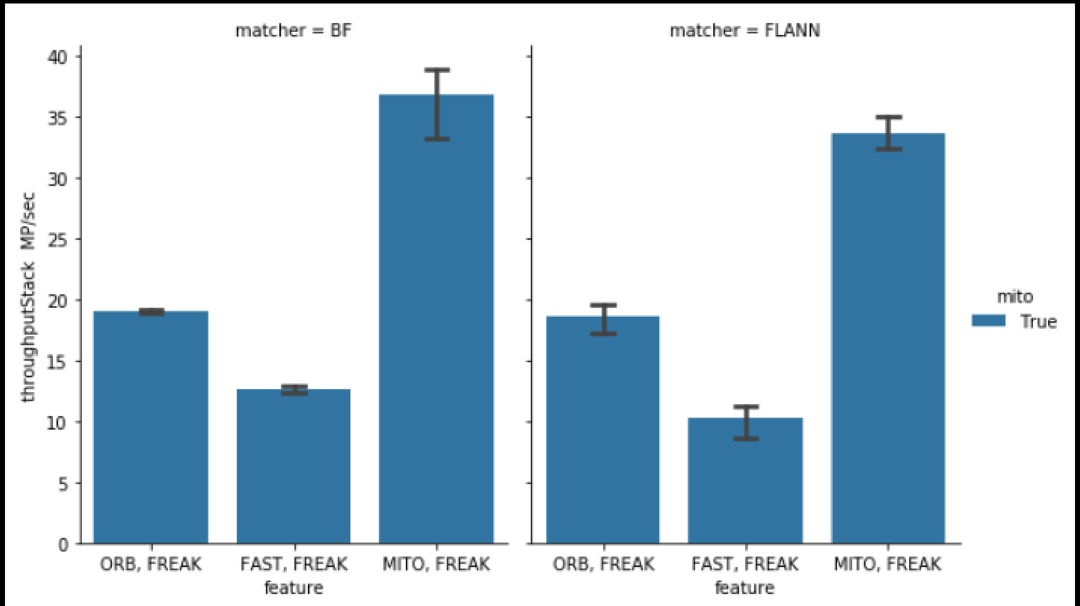


Image Alignment Comparison with MITO







Our Takeaway

The guided alignment approach using mito mask is significantly faster for all the pairwise registrations.

Using MITO + BRISK and MITO + FREAK,

average dice > .89

in > 10 second

with throughput > 11 MegaPixel/second for the whole stack

BF matcher	Feature	MITO	Dice score	Execution Time sec	Throughput MP/sec
	BRISK	FALSE	.9354	47.0052 (±1.5173)	6.7879 (±0.2170)
		TRUE	.8569	19.3020 (±0.2625)	16.5210 (±0.2256)
	ORB	FALSE	.7529	19.4427 (±1.8462)	16.4941 (±1.4953)
		TRUE	.8226	20.4218 (±0.5493)	15.6208 (±0.4259)
	FAST + BRISK	FALSE	.9184	2419.9270 (±99.9857)	0.1319 (±0.0053)
		TRUE	.8762	28.4635 (±1.2776)	11.2167 (±0.4908)
	ORB + BRISK	FALSE	.6291	16.3020 (±1.4923)	19.6693 (±1.8124)
		TRUE	.7935	16.9687 (±1.6858)	18.9180 (±1.9290)
	FAST + FREAK	FALSE	.9405	2391.9479 (±137.7484)	0.1335 (±0.0074)
		TRUE	.9140	25.1302 (±0.5)	12.6912 (±0.2498)
	ORB + FREAK	FALSE	.8320	16.6458 (±1.8088)	19.2979 (±1.9733)
		TRUE	.7637	16.8072 (±0.1365)	18.9718 (±0.1545)

FLANN matcher

Feature	MITO	Dice score	Execution Time sec	Throughput MP/sec
BRISK	FALSE	.9344	40.1145 (±0.9393)	7.9514 (±0.1887)
	TRUE	.8338	19 (±2.4111)	16.9513 (±2.0058)
ORB	FALSE	.8069	19.3802 (±1.2145)	16.4941 (±0.9979)
	TRUE	.8280	20.6875 (±1.1149)	15.4417 (±0.8082)
FAST + BRISK	FALSE	.9338	3082.2343 (±130.2627)	0.1035 (±0.0043)
	TRUE	.8784	29.6041 (±0.2350)	10.7709 (±0.0856)
ORB + BRISK	FALSE	.6297	16.9322 (±1.7772)	18.9655 (±1.9261)
	TRUE	.7648	15.2031 (±1.1735)	21.0579 (±1.6571)
FAST + FREAK	FALSE	.9450	2628.3229 (±32.5343)	0.1213 (±0.0015)
	TRUE	.9091	31.4166 (±4.7502)	10.2940 (±1.4380)
ORB + FREAK	FALSE	.8285	16.2812 (±0.0563)	19.5841 (±0.0676)
	TRUE	.7402	17.2083 (±1.2107)	18.5882 (±1.2665)

Detector	Descriptor	Matcher	Dice Score	Execution Time sec	Throughput MP/sec
MITO	BRISK	BF	.9142	7.7708 (±0.0888)	41.035 (±0.4713)
		FLANN	.9062	9.2239 (±0.7265)	34.7050 (±2.6154)
MITO	FREAK	BF	.8963	8.3697 (±0.0888)	38.0983 (±0.4027)
		FLANN	.8928	9.4843 (±0.3694)	33.6528 (±1.3213)

MONAI

Image Unsupervised Registration

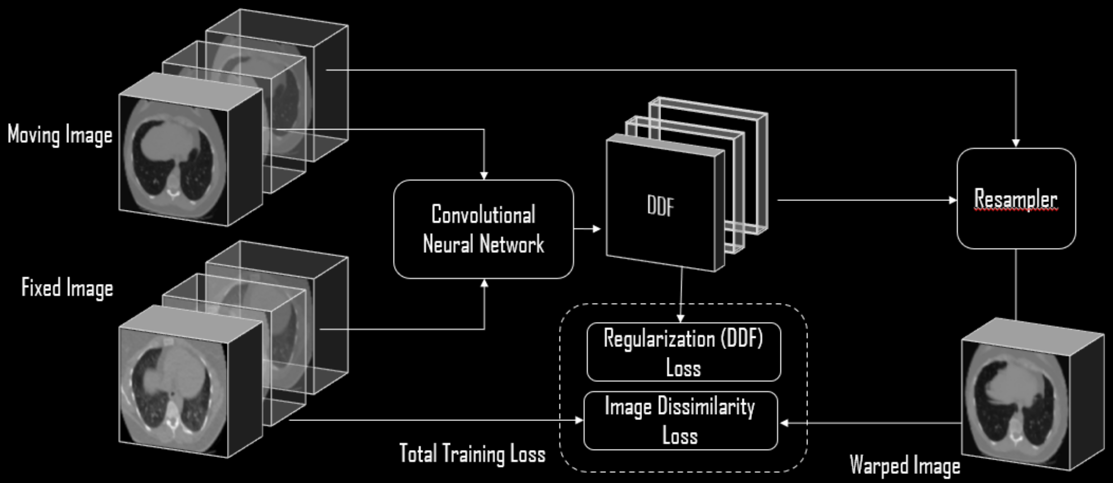
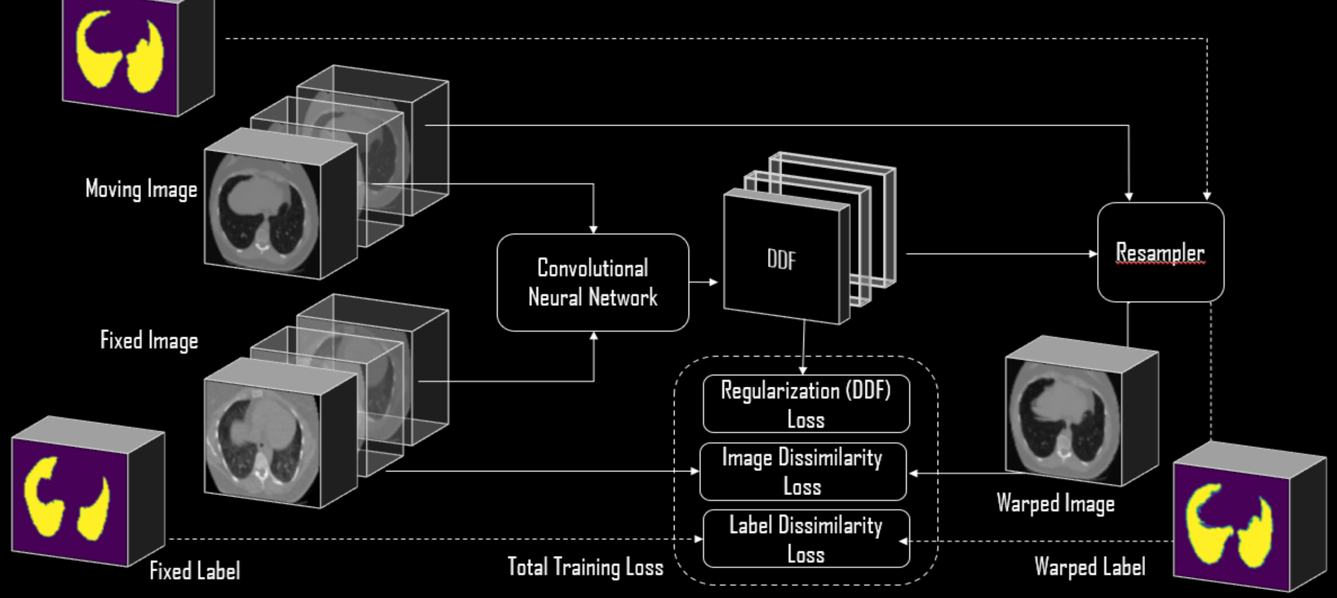


Image Supervised Registration



Label Supervised Registration

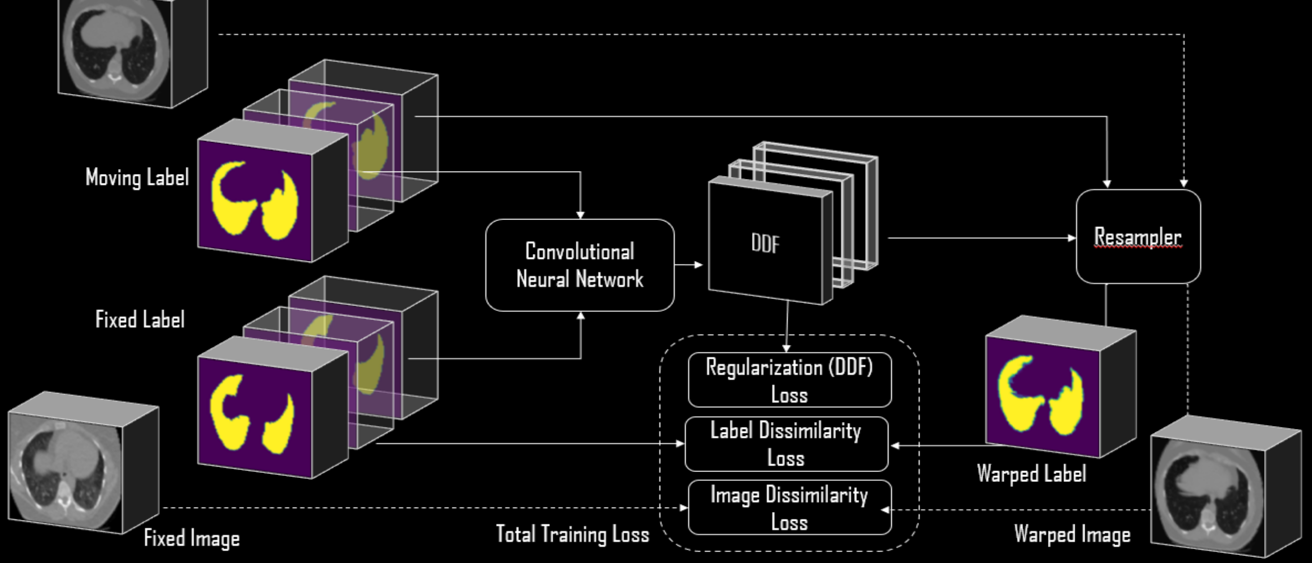
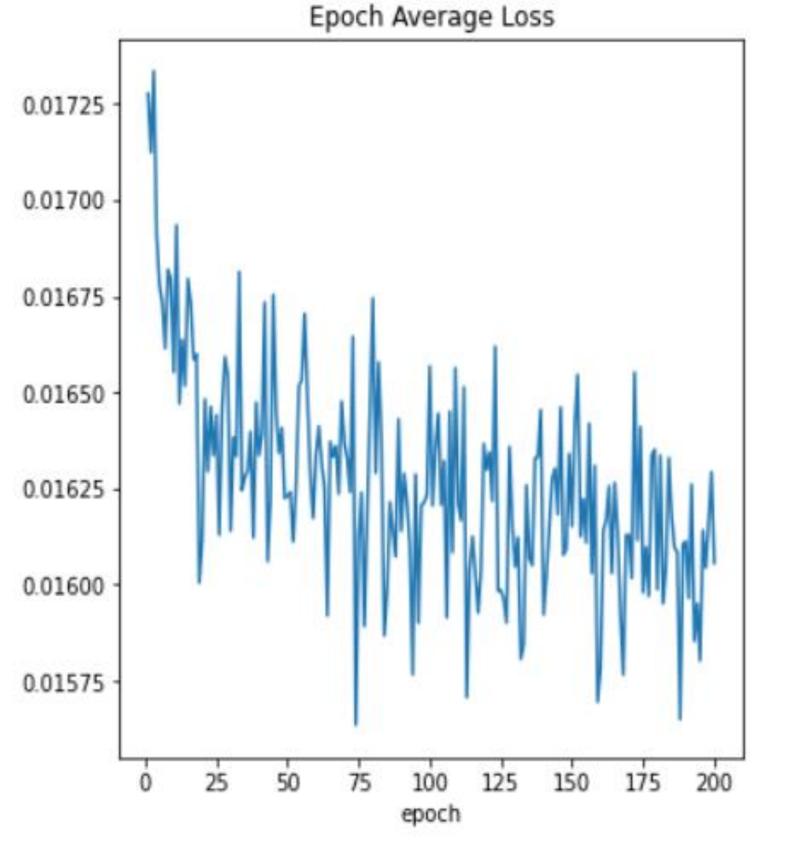
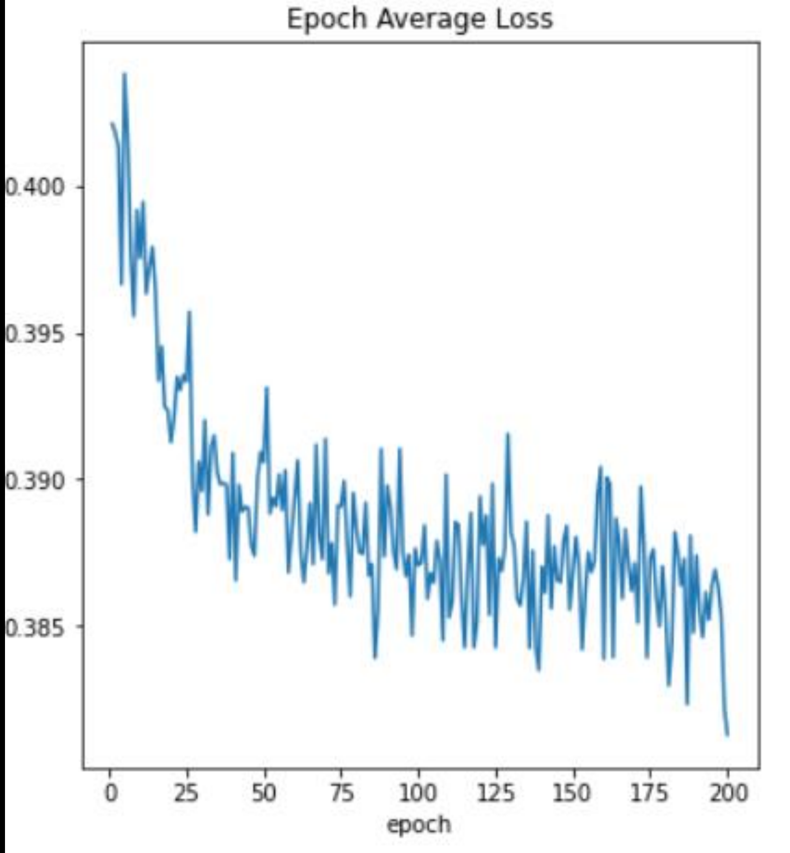


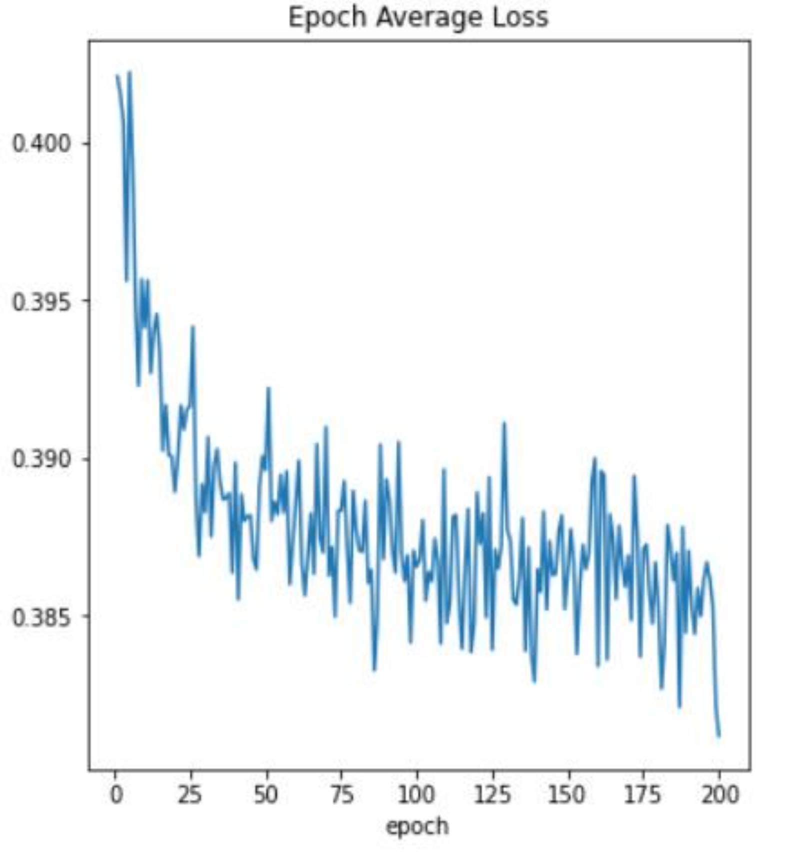
Image Alignment with MONIA



Unsupervised alignment with Image ddf

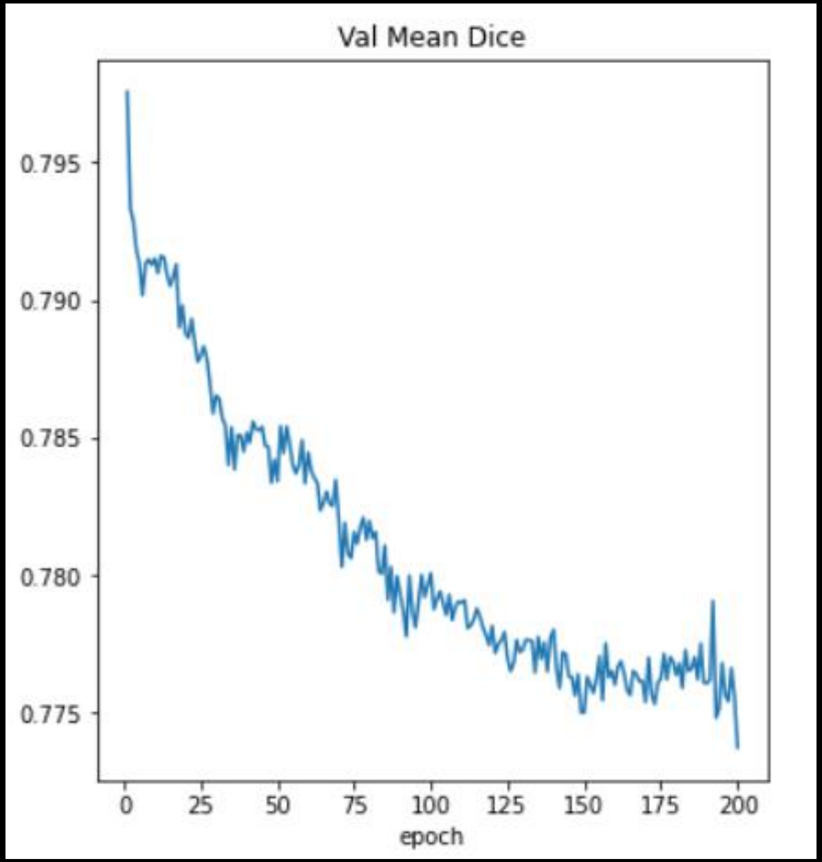


Supervised alignment with Image ddf

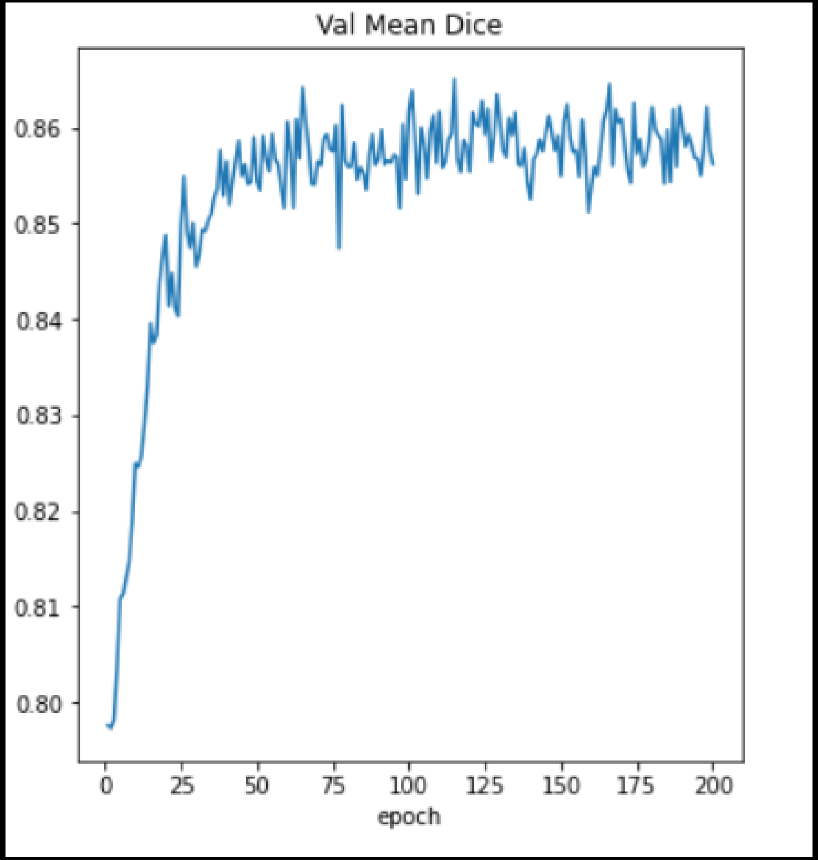


Supervised alignment with Label ddf

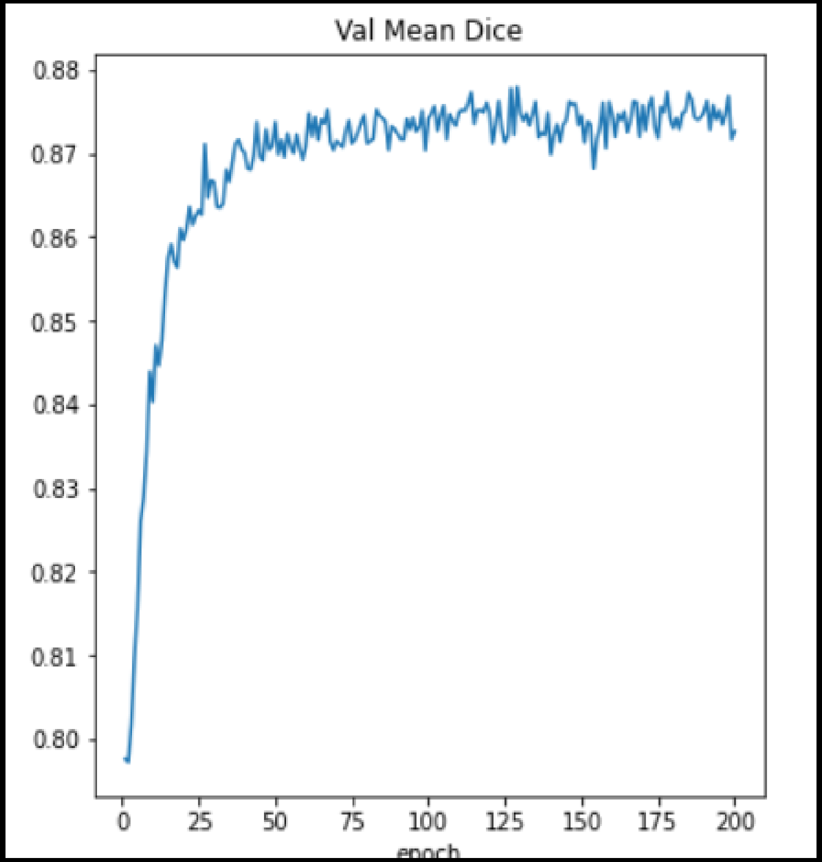
Image Alignment with MONIA



Unsupervised alignment with Image ddf



Supervised alignment with Image ddf



Supervised alignment with Label ddf

CONCLUSIONS

Adding biological features in image alignment process we have observed that

- Faster
- Alignment Score is higher
- With feature matching method we can achieve alignment in real time

THANK YOU