

EE209AS

Final Project

1/28/2019

- Option_1: Traditional CV based algorithm acceleration for license plate detection and recognition
- Option_2: Deep learning based algorithm acceleration for license plate detection and recognition
- Option_3: Acceleration for image registration operations

License Plate Detection and Recognition

- Background
 - Surveillance video can be useful in a lot of scenarios
 - A detection + segmentation + classification problem
 - Recognize license plate from still video images of CCTV

License Plate Detection and Recognition

- Dataset:
 - Application oriented license plate (AOLP) Databased by NTUST
 - <http://aolpr.ntust.edu.tw/lab/index.html>
 - <https://drive.google.com/open?id=1t2zesc4jJDkhj6lF6SeyR6iMPTHTPxfn>
- Supplement dataset:
 - License plate recognition dataset
 - https://drive.google.com/open?id=1Na_bT2pKYdEiv0UvBPwzG0_zmi8wwCNd

License Plate Detection and Recognition



Access control camera



Traffic law enforcement camera



Road patrol camera

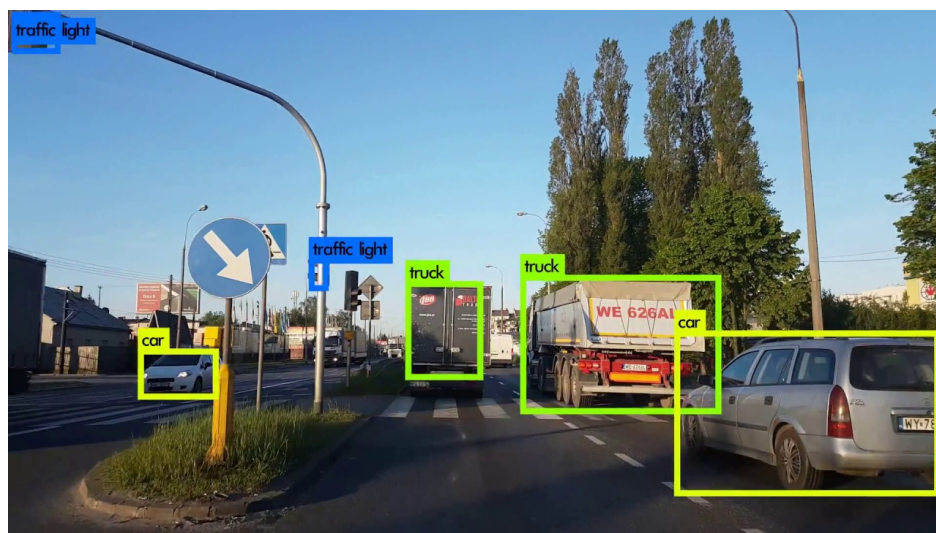
```
{
  "annotation":{
    "folder":"AOLP_LE_test",
    "filename":"1.jpg",
    "source":{
      "database":"AOLP",
      "annotation":"LE_test",
      "image":"AOLP"
    },
    "size":{
      "width":"640",
      "height":"480",
      "depth":"3"
    },
    "segmented":"1",
    "object":{
      "name":"plate",
      "platetext":"3968XJ",
      "pose":"Frontal",
      "truncated":"1",
      "difficult":"0",
      "bndbox":{
        "xmin":"173",
        "ymin":"200",
        "xmax":"316",
        "ymax":"275"
      }
    }
  }
}
```

License Plate Detection and Recognition

- Dataset:
 - Application oriented license plate (AOLP):
 - AC: 100 training + 581 testing
 - LE: 100 training + 687 testing
 - RP: 100 training + 511 testing
 - License Plate dataset:
 - 3922 images with labels
 - Not necessary to be used

License Plate Detection and Recognition

- Past work
 - 1. The recognition is often done in steps. And for each step, a (deep) model is trained.
 - 2. The model can either be of traditional CV methods, or deep learning methods.
- **References see the next page**



Step 1: Car detection



**Step 2:
License plate cropping**



**Step 3:
number recognition**

License Plate Detection and Recognition

- **Tradition methods for license plate recognition**

K. K. Kim, K. I. Kim, J. B. Kim and H. J. Kim, "Learning-based approach for license plate recognition," Neural Networks for Signal Processing X. Proceedings of the 2000 IEEE Signal Processing Society Workshop (Cat. No.00TH8501), Sydney, NSW, Australia, 2000, pp. 614-623 vol.2.

Zehang Sun, G. Bebis and R. Miller, "On-road vehicle detection using Gabor filters and support vector machines," 2002 14th International Conference on Digital Signal Processing Proceedings. DSP 2002 (Cat. No.02TH8628), Santorini, Greece, 2002, pp. 1019-1022 vol.2.

Wei Zheng and Luhong Liang, "Fast car detection using image strip features," 2009 IEEE Conference on Computer Vision and Pattern Recognition, Miami, FL, 2009, pp. 2703-2710.

C. N. E. Anagnostopoulos, I. E. Anagnostopoulos, V. Loumos and E. Kayafas, "A License Plate-Recognition Algorithm for Intelligent Transportation System Applications," in IEEE Transactions on Intelligent Transportation Systems, vol. 7, no. 3, pp. 377-392, Sept. 2006.

Anagnostopoulos, C., Anagnostopoulos, I., Psoroulas, I.D., Loumos, V., & Kayafas, E. (2008). License Plate Recognition From Still Images and Video Sequences: A Survey. *IEEE Trans. Intelligent Transportation Systems*, 9, 377-391.

- **Deep learning methods for license plate recognition**

Li, H., & Shen, C. (2016). Reading Car License Plates Using Deep Convolutional Neural Networks and LSTMs. *CoRR*, *abs/1601.05610*.

Yamwong, P., Hou, S., Wang, Z., & Zha, Z. (2018). Towards Human-Level License Plate Recognition. *ECCV*.

Xie, L., Ahmad, T., Jin, L., Liu, Y., & Zhang, S.X. (2018). A New CNN-Based Method for Multi-Directional Car License Plate Detection. *IEEE Transactions on Intelligent Transportation Systems*, 19, 507-517.

Laroca, R., Severo, E., Zanlorensi, L.A., Oliveira, L.E., Gonçalves, G.R., Schwartz, W.R., & Menotti, D. (2018). A Robust Real-Time Automatic License Plate Recognition Based on the YOLO Detector. *2018 International Joint Conference on Neural Networks (IJCNN)*, 1-10.

Option 1: Traditional CV based algorithm acceleration for license plate detection and recognition

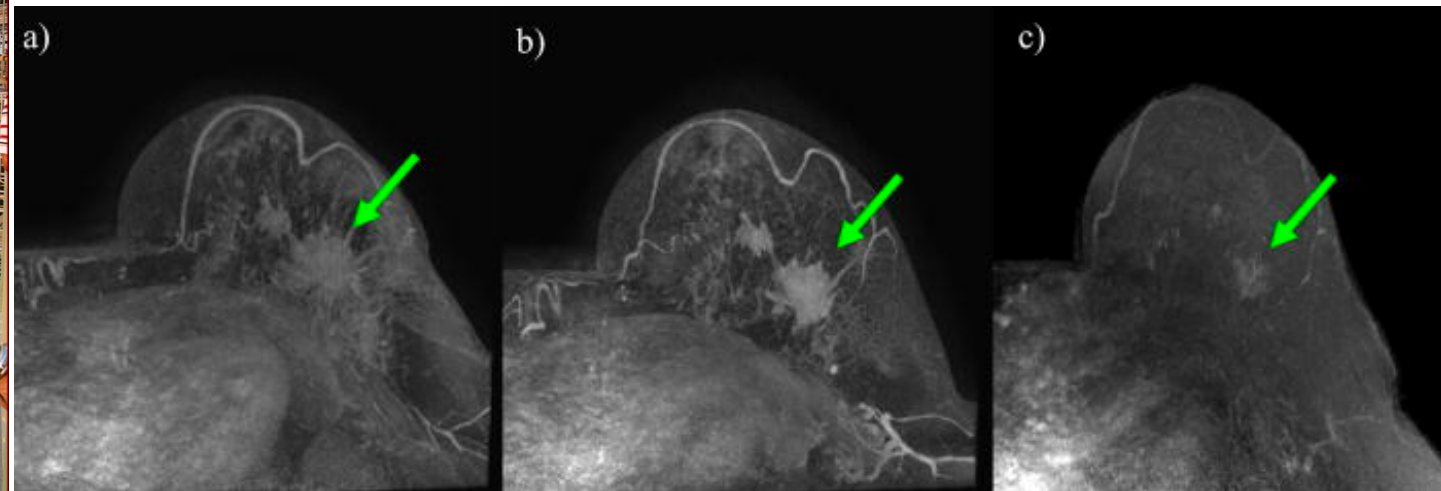
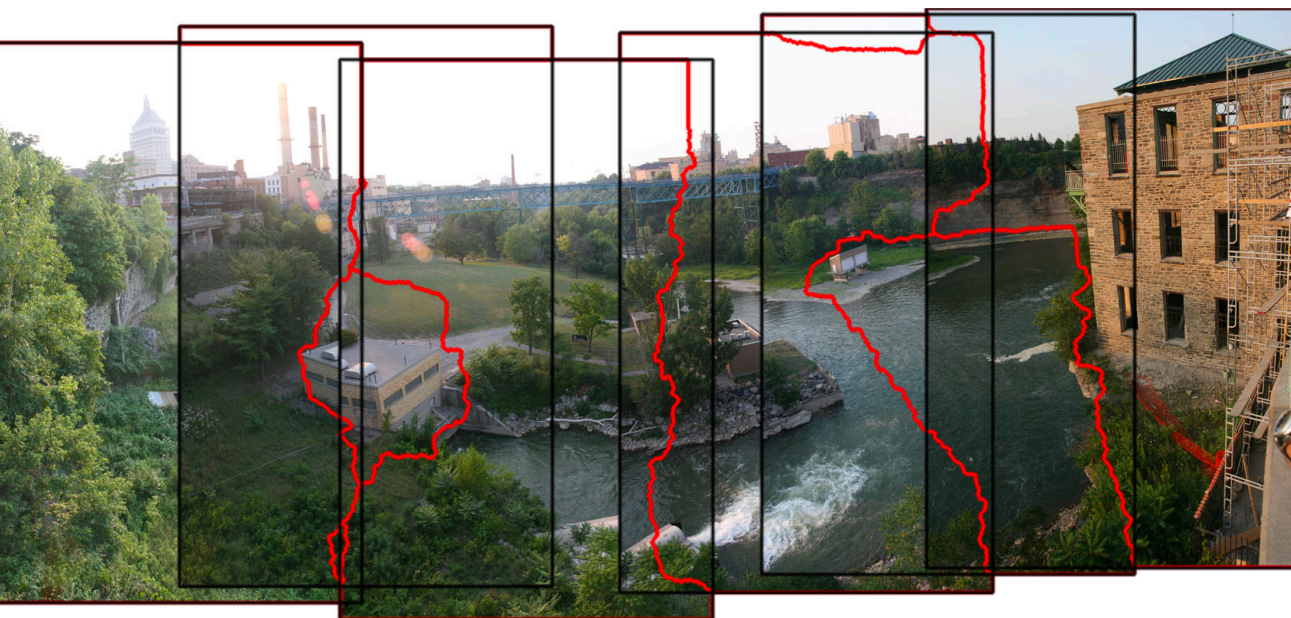
- Task
 - 1. Review traditional CV based methods for license plate recognitions.
 - 2. Build the framework for license plate recognition. The models can be self implemented or from references.
 - 3. Analyze framework and profiles the steps.
 - 4. Select one step to accelerate by using FPGA.
 - 5. Run simulations in Verilog and analyze the acceleration.

Option 2: Deep learning based algorithm acceleration for license plate detection and recognition

- Task
 - 1. Review deep learning based methods for license plate recognitions.
 - 2. Build the framework for license plate recognition. The models can be self implemented/trained or from references/trained models.
 - 3. Analyze framework and profiles the steps.
 - 4. Select one network to accelerate by network pruning and FPGA.
 - 5. Run simulations in Verilog and analyze the acceleration.

Image Registration

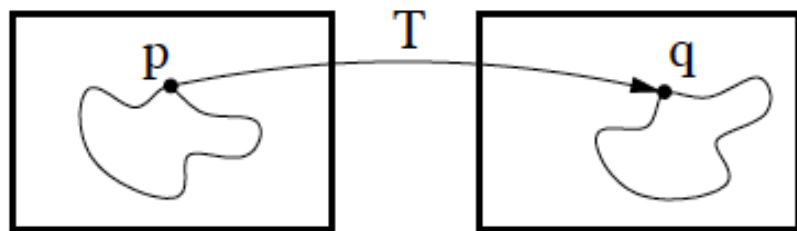
- Background
 - Finding a spatial one-to-one mapping from pixels in one image to pixels in the other image
 - Useful in a lot of scenarios



By Noso1 (talk) - Own work (Original text: I created this work entirely by myself.), Attribution, <https://commons.wikimedia.org/w/index.php?curid=12084707>

Li X, Dawant BM, Welch EB, et al. A nonrigid registration algorithm for longitudinal breast MR images and the analysis of breast tumor response. *Magn Reson Imaging*. 2009;27(9):1258-70.

Image Registration



Moving Image $I_M(x)$
 $\Omega_M \subset R^d$

Fixed Image $I_F(x)$
 $\Omega_F \subset R^d$

Finding $T_u : \Omega_F \rightarrow \Omega_M$, such that $I_M(T_u(x))$ aligns with $I_F(x)$

Solving $\hat{u} = \arg \min_u C(u; I_F; I_M)$

s.t. $C(u; I_F, I_M) = -S(u; I_F, I_M) + \gamma P(u)$

	$T_u : \Omega_F \rightarrow \Omega_M$	Formulation	# of parameters
Rigid models	Translation	$T_u(x) = x + \underline{t}$	3
	Rigid	$T_u(x) = \underline{R(x - c)} + \underline{t + c}$	9
	Affine	$T_u(x) = \underline{A(x - c)} + \underline{t + c}$	12
Non-Rigid (deformable) models	B-splines	$T_u(x) = x + \sum_{\underline{x_k \in N}} \underline{p_k} \left(\frac{x - x_k}{\sigma} \right)$	N*P
	Thin-plate splines	$T_u(x) = x + \underline{Ax + t} + \sum_{\underline{x_k \in N}} \underline{c_k} G(x - x_k)$	N*C
Non-parametric models	Non-parametric models	

Image Registration

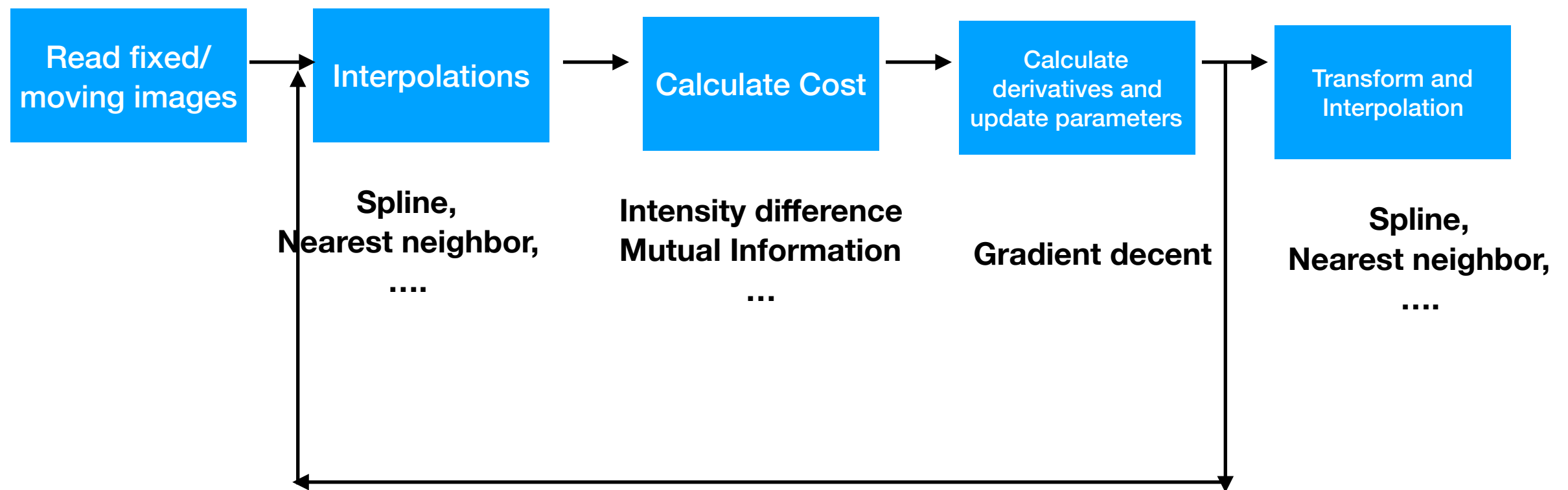
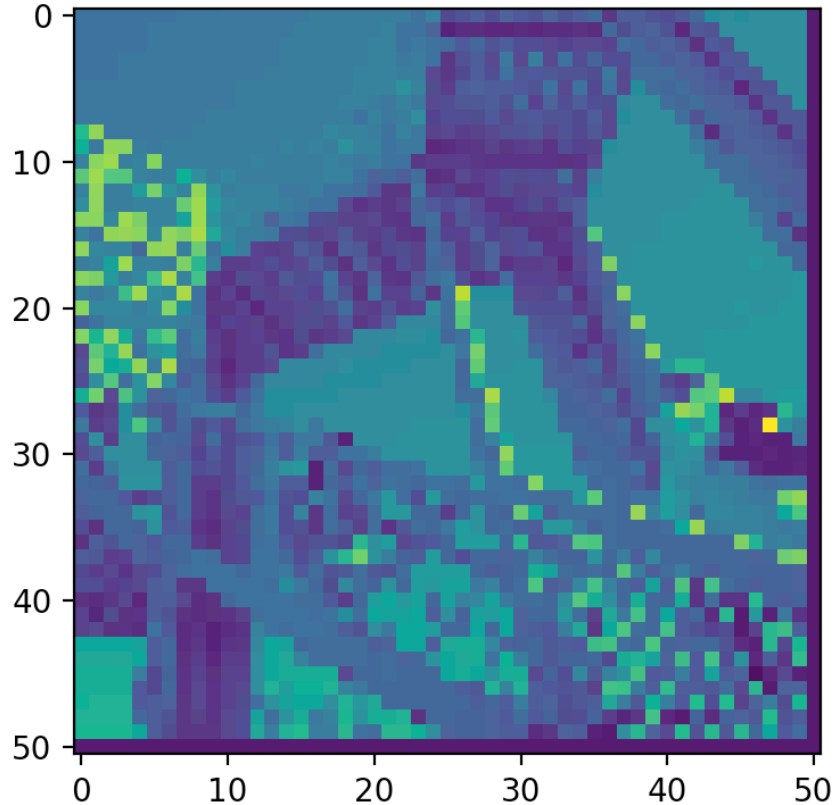


Image Registration

- Source code in Python
 - <https://github.com/pyimreg/imreg>
 - Modified and uploaded on google drive:
 - <https://drive.google.com/file/d/1jECiAbWrnxTPVhlousloYQvbnOx2YxvW/view?usp=sharing>
- We will work with rigid registration, bilinear interpolation, and intensity difference as cost function. See code for more information.
- To learn more about the code, see references we recommend as below:
 - Code implementation: S. Baker and I. Matthews. Equivalence and efficiency of image alignment algorithms. In Proceedings of the 2001 IEEE Conference on Computer Vision and Pattern Recognition, Volume 1, Pages 1090 – 1097, December 2001.
 - General registration: https://www.creatis.insa-lyon.fr/~srit/tete/2012_master_eeap_si_m5.pdf

Image Registration

image



template

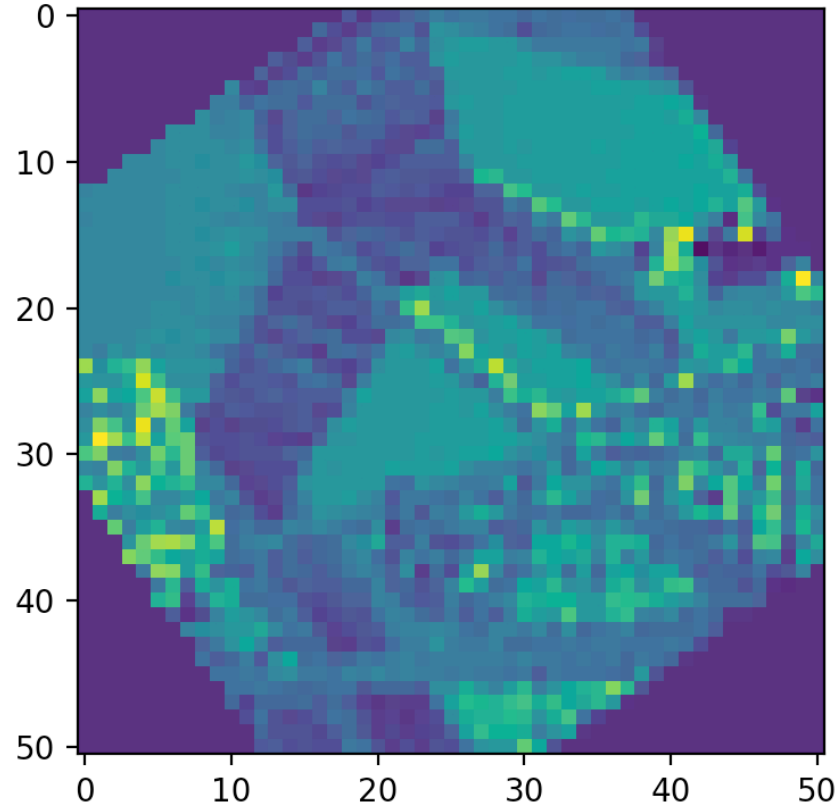
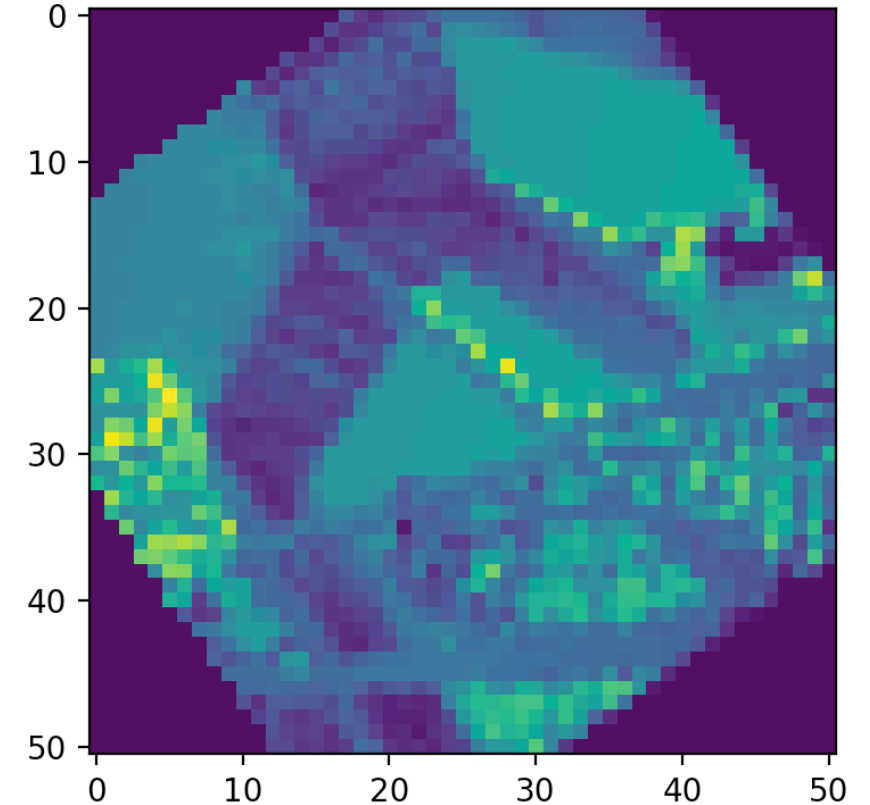


image aligned to template










$$T_u(x) = A(x - c) + t + c$$

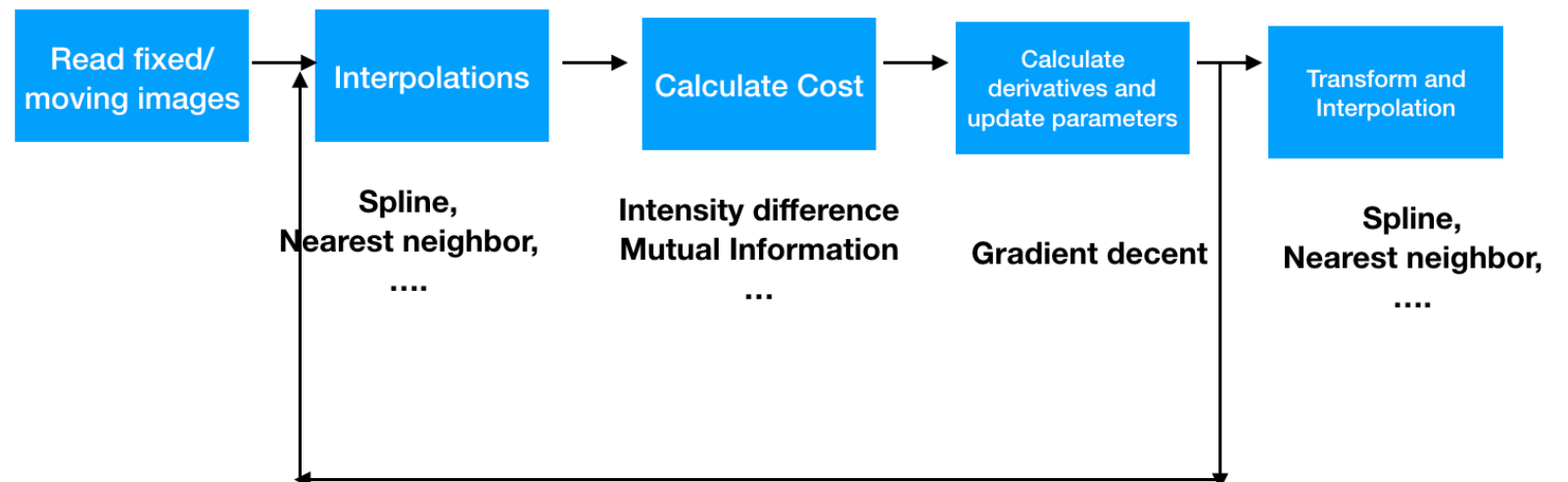
6 parameters in total for rotation, scaling, and transportation.

1756909 function calls (1748951 primitive calls) in 4.036 seconds

Ordered by: cumulative time

ncalls	tottime	percall	cumtime	percall	filename:lineno(function)
1	0.011	0.011	4.038	4.038	engine_run.py:1(<module>)
1	0.000	0.000	2.137	2.137	pyplot.py:236(show)
1	0.000	0.000	2.137	2.137	backend_bases.py:178(show)
1	0.000	0.000	1.483	1.483	backend_macosx.py:208(mainloop)
1	1.482	1.482	1.483	1.483	{matplotlib.backends._macosx.show}
1	0.210	0.210	0.654	0.654	{method 'show' of '_macosx.FigureManager' objects}
1	0.001	0.001	0.530	0.530	common.py:123(ascent)
1	0.000	0.000	0.518	0.518	pickle.py:1383(load)
1	0.117	0.117	0.518	0.518	pickle.py:851(load)
1	0.037	0.037	0.464	0.464	__init__.py:101(<module>)
2	0.000	0.000	0.442	0.221	backend_macosx.py:79(_draw)
340/2	0.003	0.000	0.416	0.208	artist.py:47(draw_wrapper)
2	0.002	0.001	0.416	0.208	figure.py:1438(draw)
8/2	0.000	0.000	0.408	0.204	image.py:123(_draw_list_compositing_images)
6	0.000	0.000	0.407	0.068	_base.py:2528(draw)
1	0.008	0.008	0.400	0.400	pyplot.py:19(<module>)
15	0.066	0.004	0.335	0.022	__init__.py:1(<module>)
1	0.002	0.002	0.309	0.309	register.py:1(<module>)
1	0.007	0.007	0.306	0.306	metric.py:1(<module>)
1	0.004	0.004	0.286	0.286	__init__.py:127(<module>)
2	0.010	0.005	0.274	0.137	__init__.py:57(<module>)
1	0.005	0.005	0.273	0.273	filters.py:31(<module>)
262144	0.157	0.000	0.267	0.000	pickle.py:935(load_binint1)
1	0.002	0.002	0.263	0.263	_ni_docstrings.py:1(<module>)
1	0.005	0.005	0.255	0.255	__init__.py:172(<module>)
1	0.022	0.022	0.250	0.250	interpolate.py:2(<module>)
12	0.000	0.000	0.209	0.017	axis.py:1182(draw)
3	0.017	0.006	0.201	0.067	__init__.py:7(<module>)
6	0.000	0.000	0.167	0.028	image.py:569(draw)
1	0.013	0.013	0.166	0.166	__init__.py:106(<module>)
526858	0.163	0.000	0.163	0.000	{method 'read' of 'file' objects}
6	0.004	0.001	0.160	0.027	image.py
6	0.015	0.003	0.155	0.026	image.py
295	0.003	0.000	0.153	0.001	{__import__}
1	0.008	0.008	0.148	0.148	colorbar.py
1	0.003	0.003	0.119	0.119	add_newcmap.py
24	0.001	0.000	0.109	0.005	axis.py:
216	0.001	0.000	0.094	0.000	axis.py:
78	0.002	0.000	0.093	0.001	axis.py:
1	0.000	0.000	0.093	0.093	pyplot.py:
13	0.000	0.000	0.089	0.007	six.py:5

名称
 __init__.py
 engine_run.py
 metric.py
 model.py
 register.py
 sampler.py
 setup.py



Option 3: Acceleration for image registration operations

- Task
 - 1. Review the code we release, and understand how it works.
 - 2. Select **one function** to accelerate by FPGA.
 - 3. Run simulations in Verilog and analyze the acceleration.

Grade Metric

- Algorithm accuracy run with PC: 30%
- FPGA acceleration design (and network pruning): 40%
- Acceleration results with simulations: 30%