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Automatic Cell Tracking in Noisy Images for Microscopic Image Analysis

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September 2014

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Submitted in part fulfilment of the requirements for the degree of
Master of Science in Computing (Artificial Intelligence) of Imperial
College London

Abstract

Acknowledgement

I offer my sincerest gratitude to life,

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Contents

1	Introduction	DRAFT I	7
1.1	Motivation	DRAFT I	7
1.2	Objectives	DRAFT I	8
1.3	Contributions	DRAFT I	9
1.4	Thesis structure	DRAFT I	9
2	Related work	DRAFT I	11
2.1	Cell detection	DRAFT I	11
2.1.1	Cell segmentation using the Watershed technique	DRAFT I	11
2.1.2	Cell segmentation using level sets	DRAFT I	12
2.1.3	Cell detection by model learning	DRAFT I	13
2.1.4	Cell detection by image restoration	DRAFT I	14
2.2	Cell tracking	DRAFT I	14
2.2.1	Tracking by model evolution	DRAFT I	15
2.2.2	Tracking by frame-by-frame data association	DRAFT I	16
2.2.3	Tracking with a dynamics filter	DRAFT I	17
2.2.4	Cell tracking by global data association	DRAFT I	18
2.3	Conclusion	DRAFT I	19
3	Detection of cells	DRAFT I	21
3.1	Cell detection overview	DRAFT I	21
3.2	Detection of candidate regions	DRAFT I	23
3.3	Inference under the non-overlap constraint	DRAFT I	24
3.4	Learning the classifier	DRAFT I	25
3.5	Feature selection	DRAFT I	26

3.6	Performance improvements	DRAFT I	27
4	Tracking of cells	DRAFT I	30
4.1	Cell tracking overview	DRAFT I	30
4.2	Joining cell detections into robust tracklets	DRAFT I	32
4.3	Global data association	DRAFT I	34
4.4	Implementation using linear programming	DRAFT I	36
4.5	Hypotheses likelihood definitions	DRAFT I	37
4.6	Computing the likelihoods	DRAFT I	39
4.7	Features for the linking classifier	OUTLINE	42
4.7.1	Estimating the velocity with Kalman filters	NEW	44
4.7.2	Gaussian broadening feature	DRAFT I	44
4.7.3	Best feature selection	NEW	45
5	Data acquisition and annotation	IN PROGRESS	46
5.1	Data acquisition and example datasets	IN PROGRESS	46
5.1.1	Datasets	NEW	47
5.2	The annotation tool	NEW	50
5.3	Annotating cell images	NEW	51
6	Experimental results	NEW	49
6.1	Cell detector	NEW	49
6.1.1	Performance	NEW	49
6.1.2	Detection accuracy	NEW	51
6.2	Cell tracker	NEW	51
6.2.1	Performance metrics	NEW	51
6.2.2	Performance	NEW	51
6.2.3	Tracking accuracy		51
7	Discussion and conclusion	NEW	52
7.1	Future work	NEW	52
	Bibliography		54

5 Data acquisition and annotation IN PROGRESS

This chapter describes the data that influenced the decisions of selecting the cell detection and tracking methods. In section 5.1 we briefly describe the imaging method used to acquire the image sequences and present some example datasets. Section 5.2 presents the data annotation tool that was developed to ease the data annotation process and in section 5.3 we discuss how the tools was used for annotating the datasets, and the difficulties that were encountered.

5.1 Data acquisition and example datasets

IN PROGRESS

As discussed in the concluding section of chapter 2 the datasets heavily influence the choice of algorithms for cell detection and tracking. Many computer vision algorithms rely on heuristics to improve their accuracy. In cell detection methods, this is obvious from the fact that a method developed for a certain type of imaging method will likely perform poorly on an image sequence of different types of cells (e.g. different shape of cells). In cell tracking heuristics help adjust the algorithms to the specific behaviour of cells that are being analysed. For example, a different tracking method could be used for images with cells that move slowly (and there is a large overlap between cells in consecutive frames) than for cells that move quickly (and there is little overlap between cells in consecutive frames).

The data acquisition process is not part of this research. However, for the reasons stated above, it is important to understand how the images were obtained and know the characteristics of the datasets. Below, we outline the image acquisition process, and then present some of the datasets we wish to analyse.

The image sequences that inspired the development of the methods describe in this thesis were acquired *in vivo*. This means that the images are obtained on living rat specimen, in contrast to *in vitro* where cells are analysed on a tissue sample in a standard laboratory environment using petri dishes and other instruments. *In vivo* analysis is preferred over *in vitro* because it is better suited for observing the behaviour of cells in its natural environment.

Ask Leo: Info about the ventilator method. Is it two-photon microscopy? What camera was used to capture the images?

More recently, the introduction of microscopes allowing for thicker tissue penetration and higher resolution (spinning-disc and two-photon microscopes), more complex tissue and organs, such as the skin, liver, brain and lung, can also be imaged. The observation of the lung was a challenge for a long time owing to motion artefacts.

The introduction of fluorescence (confocal) microscopy in combination with spinning-disc and two-photon microscopes has allowed the use of fluorescent antibodies for labelling different cell populations on anatomical structures, as well as the use of transgenic mice with fluorescent leukocyte subsets.

All the data was provided by Dr. Leo Carlin from the Leukocyte Biology Section at the National Heart and Lung Institute (NHLI)¹.

5.1.1 Datasets NEW

From the datasets provided by Dr. Leo Carlin, five have been selected to use in the evaluation of this work because of their distinct characteristics.

¹<http://www1.imperial.ac.uk/nhli/>

For each dataset, describe what it is (cell, background), characteristics (density, length, quality, artefacts), how easy/hard would they be to track, dimensions

Dataset A

This is series30green

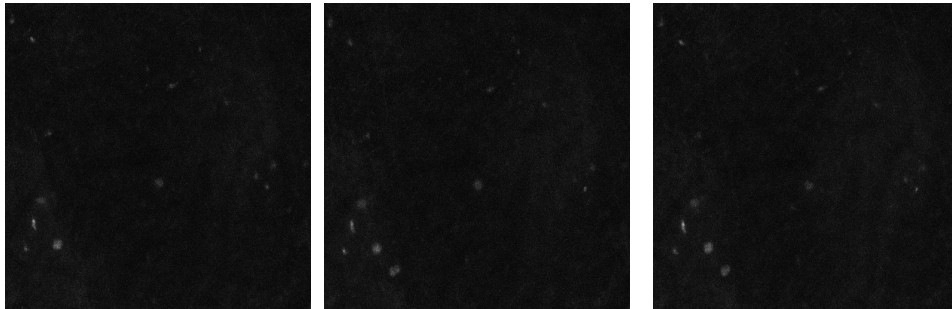


Figure 5.1: Three consecutive frames from dataset A.

This is a dataset obtained from the lung. This dataset contains a very low cell density (about 3 cells per frame). The image sequence contains 66 frames, all of which were annotated. The cells appear grey on a dark, relatively homogeneous, background. The cell boundaries smoothly blend into the background. The images are of constant quality, and there are few significant camera artefacts. The cells move slowly.

Lung for sure?

What is the difference between these cells and the ones in dataset B?

They are taken simultaneously... on is series30red the other series30green

Dataset B

This is series30red

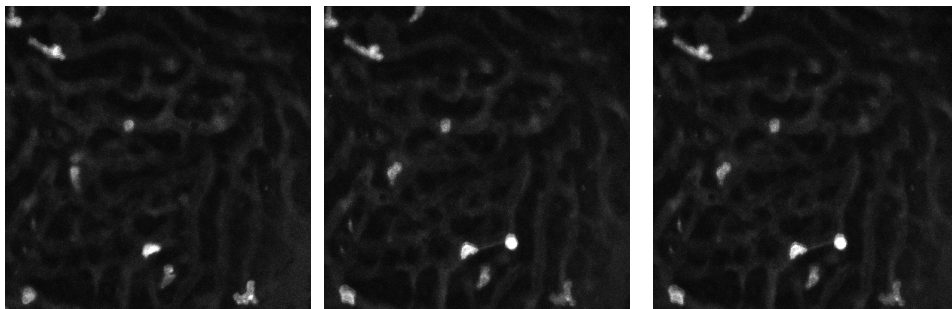


Figure 5.2: Three consecutive frames from dataset B.

This dataset is also obtained from the lung. In fact, it was obtained

Lung for sure?

simultaneously with dataset A, but represents a different types of cells .The cells appear brighter than in dataset A, but their shapes vary. Some are round and others elongated because of the tight blood vessels in which they move. In the background we can clearly discern the blood vessels in a darker grey colour. Cells in this dataset are more active in movement. The images are of constant quality, and there are few significant camera artefacts.

Ask Leo to help me specify

Are thes blood vessels?

Dataset C

This is series13green

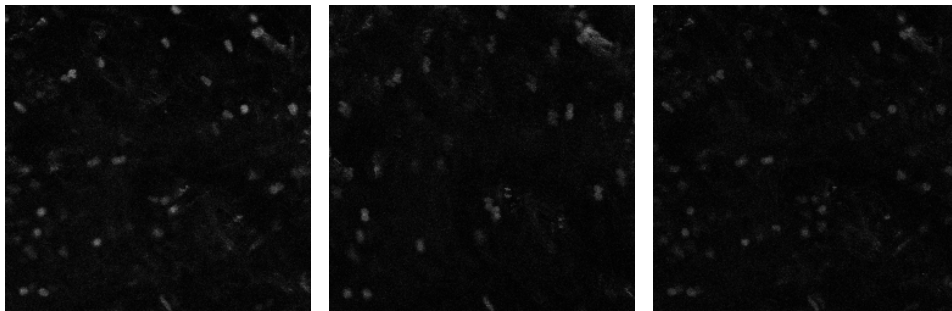


Figure 5.3: Three consecutive frames from dataset C.

Dataset D

This is series14croppedclean

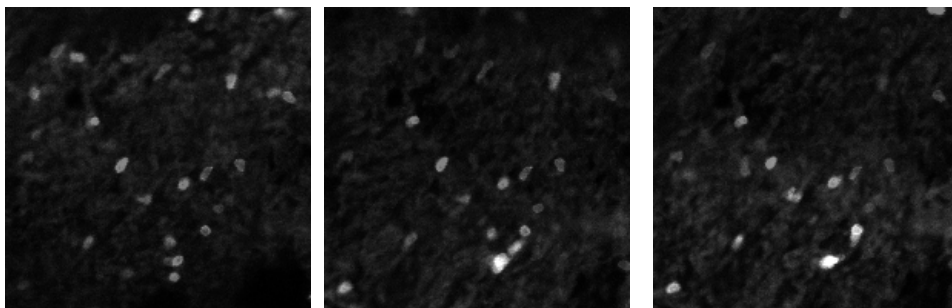


Figure 5.4: Three consecutive frames from dataset D.

Dataset E

This is seriesm170_13cropped

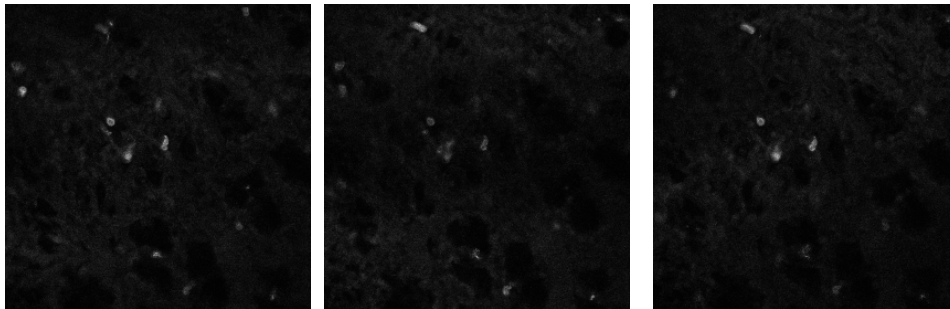


Figure 5.5: Three consecutive frames from dataset E.

rewrite about he type of cells i am tracking briefly, and focus a lot on the imaging technique. Provide examples of different images from different datasets, illustrate the problem of out of focus, the out-of-sync shutter, etc.

Original images are 512-by-512.

TODO: I need more data on the different labeled cells (red, green)

TODO: I need more data on the exact technique and aparatus used to take the images (camera, etc)

Describe the future possible improvements of the imaging technique

Write what parameters were used for the tracker

5.2 The annotation tool NEW

some notes on the importance of accurate annotation,s advantages and disadvantages of dot annotations.

Describe the requirements of an efficient cell annotation tool, such as multipreview, linking, zooming, correct interpretation and saving of the dataformat

An overview of the annotation GUI

the multiple displays filter tools for adding/deleting dots and links
simultaneous display of detections and links

5.3 Annotating cell images NEW

What follows is a description of the process of image annotation for use in the machine learning algorithm to detect cells. The image annotation, as required by Arteta's [1] algorithm, are dots on each cell of the image. The algorithm uses these dots as positive examples, and all the remaining pixels as negative examples of a cell.

We have annotated a subset of frames on the Lung dataset provided by Dr. Leo Carlin. The entire dataset is composed of 150 frames, and is divided into two channels, one for each type of cell ([.](#)). We have marked 10 cropped frames on each channel (frame 1, 14, 25, 46, 81, 115, 131, 143 and 150) of dimensions about 128×118 pixels.

The annotation was performed using a Fiji [24] tool called PointPicker [25] which is accessible from *Analyse/Tools/PointPicker*. The annotation is done by manually clicking on each identified cell. The tool outputs a *txt* file containing *x* and *y* coordinates of each annotation, the image number, as well as some other metadata that is not important for us.

It must be noted that the images are very noisy, and it is often hard to distinguish cells from non cells. Figure 5.6 displays an example of an image that was annotated. It is therefore questionable how accurately the learning method will be able to learn the idea of a cell, given that the annotations are far from perfect. It would have been much easier to perform the learning using a synthetic dataset.

The data is then loaded into MATLAB and converted into the format required by the algorithm. The data tidying is performed by the script *prepareTrainData.m*.

The feature of the tool

A user guide is provided in the appending

Briefly explain who made the annotation

Explain who reviewed them

Explain how good the annotations are

Explain if more detailed annotation would result in better results

Rewrite: This describes annotation using Fiji, which was only used at the beginning

I need to learn more about the types of cells I am tracking

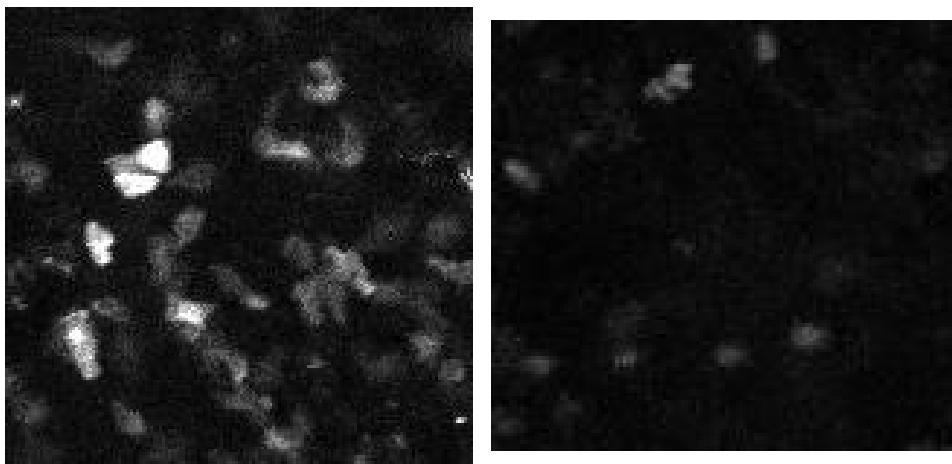


Figure 5.6: Examples of a cropped frame that was annotated for the cell detection machine learning algorithm. Each frame belongs to a different channel of the dataset.

Add appending:
User guide for the
annotation tool.
User guide for the
detector/tracker

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