

A new video analysis algorithm for the study of crowd dynamics

Jordan Osborn (jo357) Supervisor: Professor Pietro Cicutà (pc245)

April 16, 2019

A new video analysis algorithm for the study of crowd dynamics

Supervisor: Professor Pietro Cicuta (pc245)

April 16, 2019

Abstract

Contents

1	Introduction	3
2	Literature Review	5
3	Theory	6
4	Implementation	7
5	Results	8
6	Discussion	9
7	Future	10
7.1	Advantages	10
7.2	Disadvantages	10
7.3	Applications	10
7.4	Further Development	10
8	Conclusion	11
9	References	12
10	Appendices	13
10.1	Code	13

1 Introduction

In this project the technique of Differential Dynamic Microscopy will be applied to videos of crowd motion. This technique provides information about the dynamical behaviour of objects in a video without the use of image segmentation. DDM was first carried out in 2008, to analyse the dynamics of colloidal particles in Brownian motion [7]. A video of colloidal particles will be analysed and will act as a test case for the code developed in this project. Differential Dynamic Microscopy has primarily been used to analyse the motion of microscopic particles [4] [5]. This project was undertaken in order to determine the applicability of DDM to macroscopic motion i.e. crowd motion videos. The code developed as a part of this project is intended to act as a reference for further development (e.g. for real time commercial crowd analysis) and so has been developed with execution speed as well as accuracy as a priority. Certain design decisions were undertaken to achieve this. Further discussion about implementation will be carried out in section 3.

In the figure below we see an outline of how DDM is carried out in the simple case of Brownian Motion. A detailed discussion of the theory behind DDM will occur in section 3.

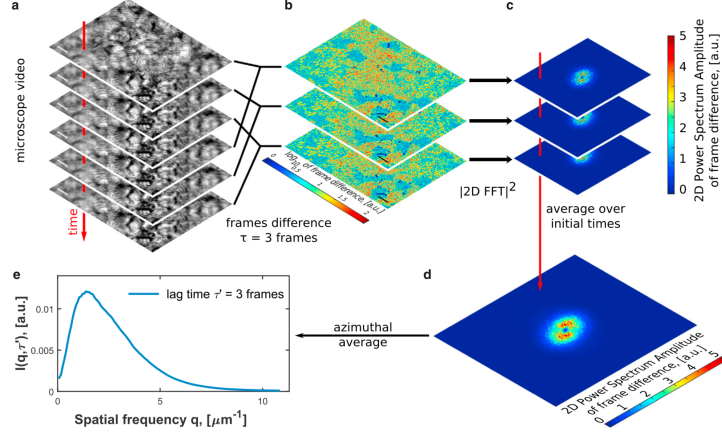


Figure 1: Provides an overview of the ddm method as applied to the analysis of collective dynamics in ciliated cells.[5]

- a we take a video of the motion we wish to analyse and convert each frame into a 2D array of gray-scale pixel intensities.
- b for each starting frame in the video we take the difference between the pixel intensities of that frame and all lagging frames. τ denotes the temporal separation of the two frames. ($\tau = 3$ frames, is shown for various start times t_0) We denote each of these differences $d(\underline{x}, t_0, \tau)$.
- c the 2D spatial Fourier transform of $d(\underline{x}, t_0, \tau)$ is then taken for all combinations of t_0 and τ . Giving us d as a function of wave-vector instead of position. $d(\underline{q}, t_0, \tau)$. We then take the modulus squared of each Fourier transform giving us a power spectrum $I(\underline{q}, t_0, \tau) = |d(\underline{q}, t_0, \tau)|^2$.
- d because the system is stationary (power spectrum should be independent of t_0 and should only depend on τ) we therefore take the average of the Fourier transforms over each t_0 . This allows us to remove the dependence of t_0 from I and also reduce the effects of experimental uncertainty.
- e in the current case the system is also isotropic and so we can then take the azimuthal average of the 2D power spectrum. This means the power spectrum is now only a function of the modulus of the wave-vector q . $I(q, \tau)$
- f the expected functional form (for Brownian Motion) of this power spectrum has been proven to be $I(q, \tau) = A(q) \cdot (1 - e^{-\tau/\tau_c(q)}) + B(q)$.

2 Literature Review

3 Theory

4 Implementation

5 Results

6 Discussion

7 Future

7.1 Advantages

7.2 Disadvantages

7.3 Applications

7.4 Further Development

8 Conclusion

9 References

- [1] Bolei Zhou, Xiaoou Tang, and Xiaogang Wang. “Measuring Crowd Collectiveness”. In: CVPR ’13 (2013), pp. 3049–3056. DOI: 10.1109/CVPR.2013.392. URL: <http://mmlab.ie.cuhk.edu.hk/projects/collectiveness/dataset.htm>.
- [2] Joseph Redmon and Ali Farhadi. “YOLOv3: An Incremental Improvement”. In: *arXiv* (2018).
- [3] B. J. Berne and R. Pecora. *Dynamic light scattering. With applications to chemistry, biology, and physics*. 1976.
- [4] Roberto Cerbino and Pietro Cicuta. “Perspective: Differential dynamic microscopy extracts multi-scale activity in complex fluids and biological systems”. In: *The Journal of Chemical Physics* 147.11 (2017), p. 110901. DOI: 10.1063/1.5001027. eprint: <https://doi.org/10.1063/1.5001027>. URL: <https://doi.org/10.1063/1.5001027>.
- [5] Luigi Feriani et al. “Assessing the Collective Dynamics of Motile Cilia in Cultures of Human Airway Cells by Multiscale DDM”. In: *Biophysical Journal* 113.1 (2017), pp. 109–119. ISSN: 0006-3495. DOI: <https://doi.org/10.1016/j.bpj.2017.05.028>. URL: <http://www.sciencedirect.com/science/article/pii/S0006349517305672>.
- [6] Bhaumik Vaidya. *Hands-On GPU-Accelerated Computer Vision with OpenCV and CUDA: Effective techniques for processing complex image data in real time using GPUs*. Packt Publishing - ebooks Account, 2018. ISBN: 1789348293. URL: <https://www.amazon.com/Hands-GPU-Accelerated-Computer-Vision-OpenCV/dp/1789348293?SubscriptionId=AKIAIOBINVZYXZQZ2U3A&tag=chimbori05-20&linkCode=xm2&camp=2025&creative=165953&creativeASIN=1789348293>.
- [7] Roberto Cerbino and Veronique Trappe. “Differential Dynamic Microscopy: Probing Wave Vector Dependent Dynamics with a Microscope”. In: *Phys. Rev. Lett.* 100 (18 2008), p. 188102. DOI: 10.1103/PhysRevLett.100.188102. URL: <https://link.aps.org/doi/10.1103/PhysRevLett.100.188102>.

10 Appendices

10.1 Code