

Observing the dynamics of waterborne pathogens for assessing the level of contamination

Isabella McKenna, Francesco Tonolini, Rachael Tobin, Jeremie Houssineau, Helen Bridle, Craig McDougall, Isabel Schlangen, John S. McGrath, Melanie Jimenez and Daniel E. Clark

Background

In environments of scarce hygiene it is of primary importance to detect potentially harmful concentrations of pathogens in drinking water. In many situations, however, accurate analysis of water samples is prohibitively complex and often requires highly specialised apparatuses and technicians. In order to overcome these limitations, a method to employ video processing to assist microfluidics water filtering apparatuses is proposed since microfluidics is an emerging area of research for waterborne pathogen sample processing and detection [1]. Through the automated analysis of videos captured at the output of such devices it is possible to extract useful information that could control an autonomous calibration, hence eliminating the need of an expert and possibly leading to the construction of readily employable water quality assessing devices.

Objectives

1. Microfluidics: design of an efficient microfluidics device

- cost-efficient
- saves resources
- separates viable pathogens from harmless particles

2. Analysis: incorporate optical system to analyse the water sample

- automated detection
- classification based on object behaviour during physical sorting

Microfluidics

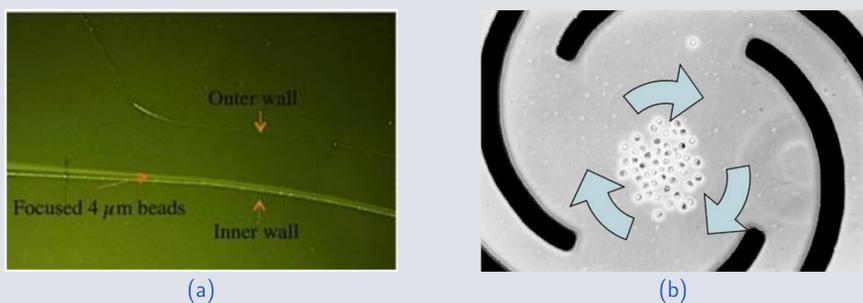


Figure 1: Microfluidic design: (a) illustrates how particles of a particular size are sorted into a narrow size band, relative to the width of the channel, and can therefore be concentrated and collected by appropriate design of the outlet area. (b) shows the output of a DEP electroration device. The electrodes (black) generate an electric field such that the particles are kept in a specific area, but can rotate within it [2].

■ **Passive hydrodynamics:** suitable flow rates are used to force particles with different size and deformability into different channels, therefore it is possible to sort viable from non-viable pathogens. Helpful for early determination of pathogen presence.

■ **Dielectrophoresis:** Biological cells are polarisable and therefore can be manipulated and trapped using an inhomogeneous electric field. Since viable and non-viable pathogens show different behaviours under the force of the same electric field, tracking with different motion models can help to detect and analyse the viability of the cells in the sample.

Object detection

1. **Binarisation:** The input image is made binary via thresholding.

2. **Circle detection:** circular Hough transform: given an image $\mathcal{I} \in \mathbb{R}^{n \times m}$, a votes array $V_g \in \mathbb{R}^{n \times m}$ for each guess radius r_g is computed as follows:

$$V_g = \sum_{i=1}^k C(p_i, r_g),$$

where $C(p_i, r_g) \in \mathbb{R}^{n \times m}$ is an array of ones on the perimeter of a circle with center p_i and radius r_g and zeros everywhere else. k is the number of perimeter candidate pixels. In every vote array V_g , those elements that are over a certain threshold determine a detected circle in the image \mathcal{I} with the coordinates of such an element as its centre and r_g as its radius.

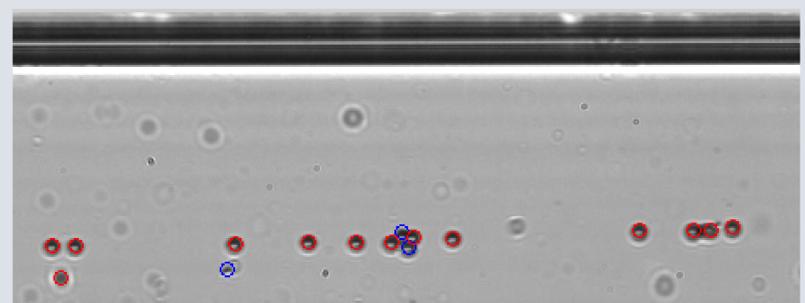
3. **Classification:** The circle detection provides not only the position of the detected objects but also their radius. Thus, one can classify particles according to their surface area.

4. **Cluster separation:** To locate objects within an estimated agglomerate, a small subsection of the image containing the agglomerate is convolved with a circle having the mean size of the pathogen of interest. The position and radius that yields the highest value in the convolved image are taken as centre and radius of a detected object. The detected object is then subtracted from the image and the process is repeated until the remaining agglomerate has an area which is considerably less than the mean size of a pathogen.

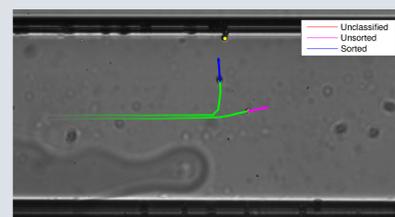
Object tracking and classification

- Multi-object filtering using Hypothesised filter for Independent Stochastic Populations (HISP) [3]: Approximated but tractable version of a multi-object Bayes filter.
- Object classification using different motion models in the filter, so the likelihood of a behaviour gives an estimate about the quality of an object.

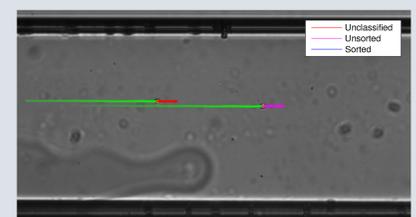
Results



(a) ○: detections using Hough transform alone.
○: detections in object clusters



(b) Tracking: the blue target was trapped in the electromagnetic field, the magenta object keeps moving to the right.



(c) Tracking: here, nothing was trapped in the field, the incoming red target is still unclassified.

Figure 2: Detection (a) and tracking/classification results (b),(c) based on real data acquired from a microfluidics device. Two behaviours were analysed: turning upwards towards the electromagnetic field, and heading onwards to the right. Tracks are shown in green, whereas unclassified objects are marked in red, sorted in blue and unsorted in magenta.

Conclusion

- Microfluidics devices yield high portability and easy employability.
- Video processing helps to assess water contamination quickly and accurately.
- Different classifications:
 1. physical separation of objects with different physical properties (size, deformability)
 2. classification by size using the proposed detection method
 3. classification by object behaviour (cell trap using an electromagnetic field)

REFERENCES

[1] H. Bridle, B. Miller, and M. P. Y. Desmulliez.

Application of microfluidics in waterborne pathogen monitoring: A review. *water research*, 55:256–271, 2014.

[2] Andrew D Goater, Julian P H Burt, and Ronald Pethig.

A combined travelling wave dielectrophoresis and electroration device: applied to the concentration and viability determination of cryptosporidium. *Journal of Physics D: Applied Physics*, 30(18):L65, 1997.

[3] Jérémie Houssineau and Daniel E. Clark.

Hypothesised filter for independent stochastic populations. arXiv: 1404.7408, 2014.

Acknowledgements

Helen Bridle, John McGrath and Melanie Jimenez are supported by STFC, the EU Aquavalens project and Scottish Water.

Jeremie Houssineau and Daniel E. Clark are supported by DSTL Task ED TIN 2-3. Isabel Schlangen has a PhD scholarship from the Edinburgh Super-resolution Imaging Consortium (ESRIC).

Craig McDougall is supported by the EPSRC as a post doctoral researcher.

Daniel Clark is supported by the EPSRC/Dstl University Defence Research Centre on Signal Processing (UDRC) Phase 2 (EP/K014227/1).