Convolutional Neural Networks can Track the Radius Evolution of Levitating-Evaporating Microdroplets

Kwasi Nyandey[1,2] Gennadiy Derkachov[1] and Daniel Jakubczyk[1]

[1]Institute of Physics, Polish Academy of Sciences, Al. Lotników 32/46, 02-668 Warsaw, Poland

[2]Laser and Fibre Optics Centre, Department of Physics, School of Physical Sciences, College of Agriculture and Natural Sciences, University of Cape Coast, Cape Coast, Ghana

Introduction

The existence of micro-particulate materials in the atmosphere is universal with a profound impact on everyday life. Their studies have proliferated in recent years because of the possibility to trap/isolate and investigate single particles from ensembles or bulk materials regardless of their physical form. Electrodynamic trapping is a method of combining AC and DC voltages to levitate a charged microdroplet/particle. Its vertical movement is then controlled by combining the DC voltage and CCD imaging of the droplet position to stabilise it at the centre of the trap [1]. The stabilisation involves continuously balancing the evaporating charged droplet's weight with the DC voltage. The measured voltage can be used to evaluate the droplet mass-to-charge ratio leading to the determination of droplet radius evolution. This method's accuracy is however, significantly limited by the accuracy of the stabilisation loop and requires a different approach to determine the droplet's charge as well as calibration [2]. Hence it is not a stand-alone method. Other well established methods of droplet/particle investigations are mechanical [3] - based on the measurement of drag force on particles and determination of particle size and interferometric particle characterization [4]. In these methods data is acquired and analysed off-line by comparing light scattering patterns with a library of theoretically generated patterns. This does not enable the investigation of transient phenomena such as Coulomb explosion or phase transitions during droplet evaporation.

We present an alternative method – a first-approach – which is fast and can be applied to evaporating microdroplets (refractive index known a priori) within a wider range of radii while reducing the processing time to practically online and retaining higher accuracy of droplet size measurements.

Method

Experiment

- A quadrupole type of electrodynamic trap was developed (see details in [2]) which is suitable for angle-resolved elastic light scattering measurements.
- The trap was kept in a climatic chamber at 21^{o}C and droplets were introduced on demand into the trap with a piezo injector (see details in [2]).
- A single droplet was trapped at a time (Fig 1) and kept at the centre of the trap by a stabilisation loop (see [2] for details) and a plane-polarised red laser (658 nm, ~10 mW power and ~ 1 mm beam diameter) was used to illuminate it. A confocal imaging system enable the projection of the light scattering pattern onto a CCD. The patterns were recorded around the azimuth angle of 90 ± 0.1^{o} to the illumination direction.

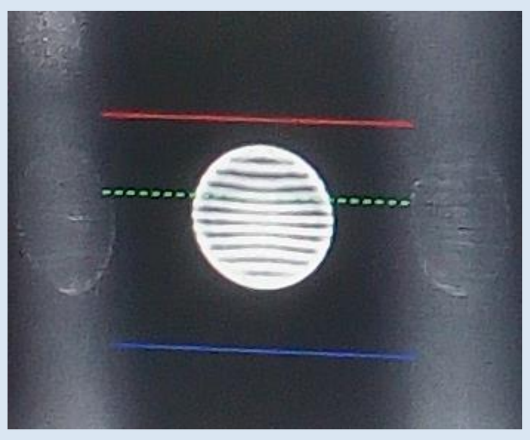

Fig 1: Single microdroplet in the trap

- A 14-bit colour camera (Pike F-032C, AVT, 640 x 480 pixels and 7.4 µm pixel size) was used to record the patterns. We recorded movies (@ 75 fps) of the patterns over the entire evolution of the evaporation, extracted and cropped into 221x501 images, (see Fig 2 (a) and (b) and histograms below.

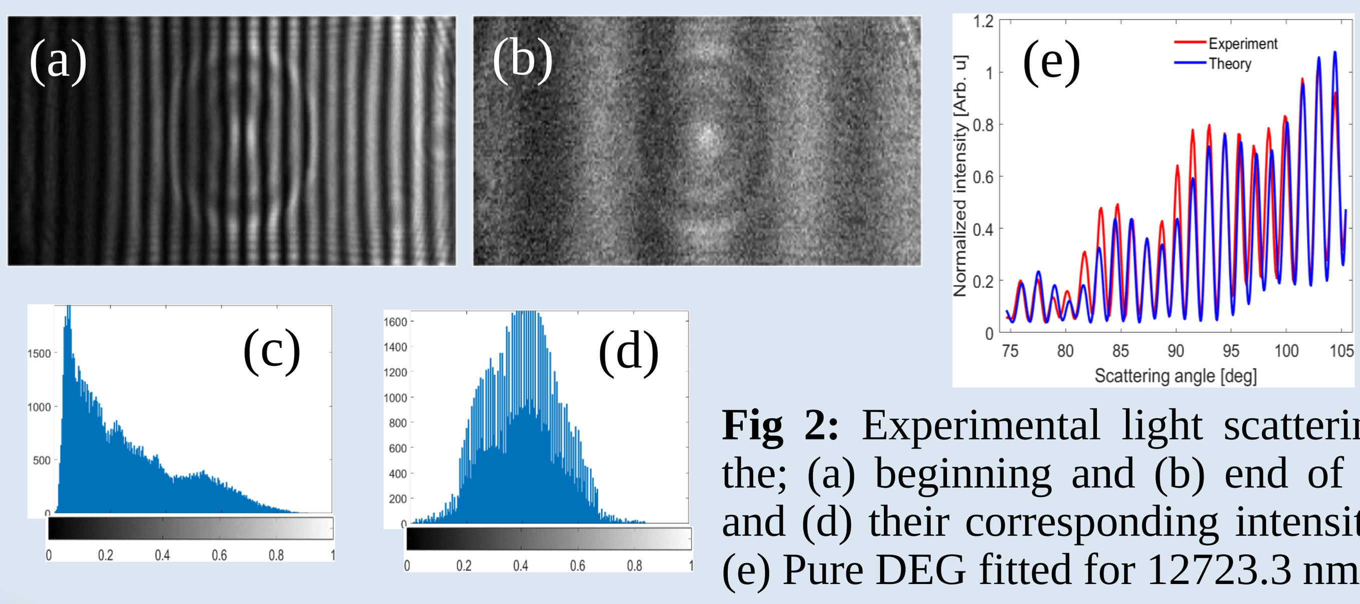

Fig 2: Experimental light scattering patterns at the; (a) beginning and (b) end of evolution. (c) and (d) their corresponding intensity histograms. (e) Pure DEG fitted for 12723.3 nm droplet.

Neural network architecture and training

- We designed a 41-layer convolutional neural network (Fig 3 (a)).
- We used Mie-theory to obtain a good fit (Fig 2 (e)) to the experimental data and generated theoretical light scattering patterns (Fig 3 (b)).
- We divided the radii range 1 – 30 µm into 976 classes with a class interval of 30 nm and generated 2000 patterns within each class.
  - Random noise (Fig 3 (c)) was multiplied by the patterns (Fig 3(d)) to mimic the electronic noise and adjust the intensity histograms (shown below) of the images.
  - For training we divided the whole data into training and validation sets. Then we generated the test set within the same radii range but without labelling or grouping into classes.
  - The trained network was used to classify the test set and experimental data from pure droplets and droplets with fewer 450 nm polystyrene nanoparticles (1:9 volume ratio).

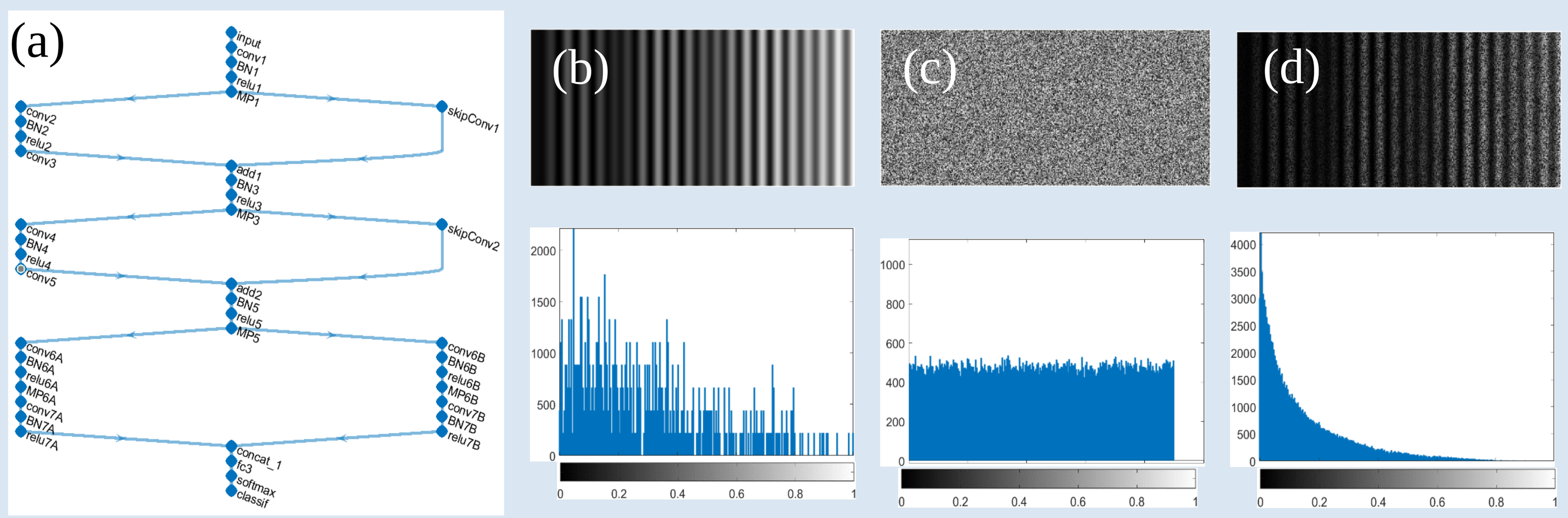

Fig 3: Theoretically generated; (a) light scattering pattern (b) random noise and (c) elementwise multiplication of (a) and (b). Their intensity histograms shown (bottom panel).

Results

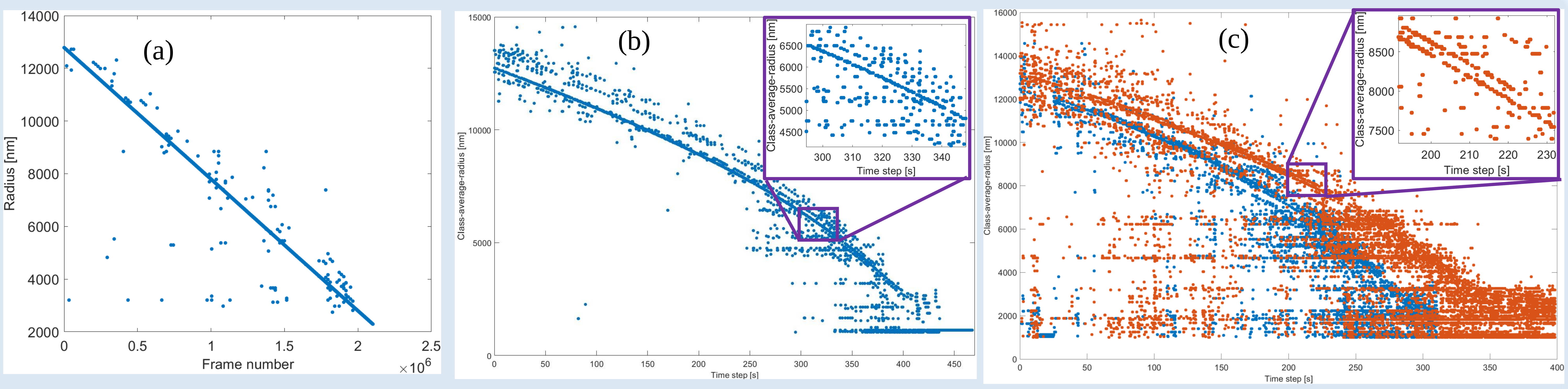

Fig 4: Classification of light scattering patterns from microdroplets; (a) theory (b) experiment (pure diethylene glycol) and (c) glycol with polystyrene nanoparticles.

Conclusions

- We trained convolutional neural network to track the radius evolution of levitating-evaporating microdroplets.
- For pure liquids, a single and main branch of evaporation rate was obtained (Fig 4 (b) and inset)
- For droplets with fewer inclusions, several discontinuous branches of evaporation (Fig 4 (c) and inset) were obtained due to the distortion of the light scattering patterns by the inclusions.

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