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Particle and salinity sensing for the marine environment via deep learning using a Raspberry Pi

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Abstract
The identification of mixtures of particles in a solution via analysis of scattered light can be a complex task, due to the multiple scattering effects between different sizes and types of particles. Deep learning offers the capability for solving complex problems without the need for a physical understanding of the underlying system, and hence offers an elegant solution. Here, we demonstrate the application of convolutional neural networks for the identification of the concentration of microparticles (silicon dioxide and melamine resin) and the solution salinity, directly from the scattered light. The measurements were carried out in real-time using a Raspberry Pi, light source, camera, and neural network computation, hence demonstrating a portable and low-cost environmental marine sensor.

1. Introduction

It is estimated that around 35,000 tons of microplastics are present in the world’s oceans [1], with trillions of microbeads entering the marine environment daily in aquatic habitats of the United States alone [2]. These microplastics can arise from products such as cosmetics, toothpaste and face scrubs [3, 4], which contain microbeads, but can also be formed from the breakdown of larger plastics already discarded into the sea [5, 6]. Microplastics can have a direct negative impact on marine organisms [7, 8], and impact other marine life through transfer via the food chain [9, 10]. They have been found in fish and bivalve organisms, and have been shown to have negative effects on zooplankton and oysters [11–16]. Table salt from around the world has been found to contain microplastics [17, 18], and the sea salt contamination, by plastic itself, has been shown to be an indicator of plastic pollution. Drinking water can also contain microplastics [19], and the potential impact on humans has been discussed [20, 21], with specific negative impacts on epithelial inflammation [22] and muscle cell behaviour [23].

Monitoring such particles is necessary to help determine origin and distribution, whilst also providing data for mitigating the effects of plastic pollution [24]. Since microplastics can reach the marine floor, having been found in sediments at depths down to 5000 m [25], and in deposit feeders that ingest sediment [26], it is therefore important to monitor plastics before they reach the marine floor. Such a sensing device must have the capability to identify the different types of microplastics and natural occurring particles, such as sand, in order for accurate monitoring. However, a significant obstacle in monitoring such a global problem is the lack of a reliable portable and low-cost method for characterisation of the pollution particles. Manta nets [27] can be used to collect plastic particulate matter from the marine environment of sizes down to ~333 μm, with additional laboratory sieving used to separate out smaller micro particles [28, 29], and material characterization carried out subsequently using a range of spectroscopic and imaging techniques [30–34]. Such collection and characterization methods are extremely time-consuming and expensive, and hence alternative methods are required.

A holographic technique that involves analysing the scattered light from particles, has shown the potential for the characterisation of particle contaminants in water [35]. Scattered light from particles is dependent on the
illumination wavelength and on the particle parameters, such as shape, size, refractive index and composition [36, 37], therefore such parameters can be inferred from analysis of the scattered light in certain cases, via comparison to theoretical calculations. In the case of light scattering from a single homogenous sphere, a full electric field calculation, for example via Mie theory, can be used to produce a simulated scattering pattern. However, the calculations become rapidly more complex as the number of particles is increased, particularly if the particles are not identical. Crucially, however, the inverse calculation is what is needed, as the particle parameters should be determined directly from the scattering pattern. Although particle monitoring from the particles are not identical. Crucially, however, the inverse calculation is what is needed, as the particle parameters should be determined directly from the scattering pattern. Although particle monitoring from observation of the scattered light has been demonstrated in [35, 38], such methods require simulations and lack the flexibility for identification of non-spherical particles. Ideally, the technique should be able to determine the parameters for many particles simultaneously, whilst also being robust enough to deal with real-world effects such as non-spherical particles, variability in light sources and optics, and variability in the aqueous environment.

Deep learning, which is an approach based on the application of neural networks (NNs) [39–41], has already enabled advances in imaging [42, 43] and enabled automated classification of objects in images [44, 45], such as label-free cell classification [46], as well as object classification through scattering media [47–49] and through scattering pattern imaging [50, 51]. Using NNs to determine particle size and refractive index from their scattering pattern was proposed by [52] and has been subsequently demonstrated experimentally on colloidal spherical particles [53–56], showing that NNs can bypass the need to develop complex modelling [57]. Moreover, the ability to update a NN [58], for example to monitor additional particles without the need to physically change a sensor, makes such an approach particularly desirable, especially when implemented on a micro-computer, such as a Raspberry Pi [59, 60].

In our previous work, we were able to use a NN to identify single particles of polystyrene and silicon dioxide on a glass substrate, and we demonstrated the ability to use a NN on a desktop computer for the real-time identification of a range of real-world airborne pollution particles (diesel soot, wood ash and pollen) on a glass substrate, directly from their scattering patterns, with each identification taking less than 50 milliseconds [61]. Others have demonstrated the combination of holography and deep learning, for the retrospective (i.e. not real-time) classification of particles in water, using a Raspberry Pi for data collection and with the neural network instead run on a desktop computer [62]. In this work, we demonstrate a Raspberry Pi-based sensor, which runs a neural network, loaded onto it via Wi-Fi, to run in real-time and classify the concentrations in water of 5 μm silicon dioxide (a type of sand) and 8 μm melamine resin (a type of plastic used for tableware [63], which has also been found in fish [64]) microparticles.

Because water salinity can impact on the health of marine life, and is a commonly used ocean parameter to study the effects of climate change [65], the ability to monitor the salinity without the need for additional electrical conductivity devices would be an extra benefit of using the sensing technique documented in this work. We thus also show that it is possible to determine the salt concentration of the water in which 8 μm melamine resin microparticles are present. In addition, we demonstrate the robustness of the NN, by performing a second set of measurements 20 days after the NN was trained, and after deconstructing and rebuilding the experimental setup, hence proving the potential for portable and low-cost sensing.

1.1. Sample preparation

Silicon dioxide microspheres of size 5 μm ± 100 nm (Sigma Aldrich, Product number 44054) and melamine resin microspheres of size 8 μm ± 200 nm (Sigma Aldrich, Product number 95523), with dimensions measured using a Coulter MultiSizer II, were deposited via pipette into deionized water-filled glass cuvettes, each of external size 12.5 mm × 12.5 mm × 45 mm, with an optical interaction length of 10 mm. To mimic seawater, saline samples that were used for NN training were prepared by adding salt (sodium chloride) to deionised water-filled cuvettes in steps of 10 ppt (parts per thousand by mass, where 1 ppt is approximately 1 psu (practical salinity unit) [66]), from 0 ppt up to 100 ppt, and 0.1 ppt of 8 μm-sized melamine resin microparticles was added to all samples. Additional cuvettes of deionized water were filled with different concentrations of mixtures of 5 μm silicon dioxide and 8 μm melamine resin microparticles, to give concentrations in the sample solution (referred to here as actual solids concentration) in the range of 0 to 0.1 ppt, in steps of 0.0125 ppt.

1.2. Experimental setup

The schematic of the experimental setup in figure 1 shows light from a ~1 mW laser diode operating at 650 nm that has been focused into the cuvette using a 2.5 cm focal length lens. This produced a spot size of approximately 20 μm by 10 μm inside the cuvette. The scattered light from the microparticles was projected onto a white polyester screen 1.5 cm from the cuvette, and subsequently imaged by a CMOS camera (Raspberry Pi Camera Module, CSI-2, 3280 × 2464 pixels), placed 5 cm away. The total volume of the focal region was therefore considerably larger than the volume of a single sphere, enabling the potential for measuring larger particles from
the same sensor design. The camera was connected to a Raspberry Pi 3 Model B+ computer to allow real-time capturing of scattering patterns, every 50 milliseconds, with an exposure time of 20 milliseconds. The images were then transferred to a desktop computer that had an NVIDIA Titan Xp GPU. One hundred scattering patterns were recorded for each of the samples stated in section 2.1 by interchanging the cuvettes in the setup. Each cuvette was shaken by hand prior to placing in the imaging setup. Once the NN was trained on the GPU, the NN was transferred via Wi-Fi to the Raspberry Pi, where it was subsequently used to conduct real-time measurements on scattering images. Here, the NN outputs corresponded to the microparticle mixture concentration, and in the second part of the work, the salinity of the water. The experiments were carried out at room temperature (22 °C).

1.3. Neural network
A convolutional neural network was used, which is a type of NN designed mainly for image processing [57, 67], with a regression output. The regression output enabled the capability for the NN to produce a continuous output within a certain range [68]. The NN framework was Tensorflow [69] and was trained on a desktop computer with an NVIDIA Titan Xp graphics processing unit (GPU). Figure 2 shows a schematic of how the NN was used in this work. Owing to the restriction in random-access memory (RAM) that was available for the NN to compute on the Raspberry Pi (1 GB), the input images were cropped such that only one quadrant of the scattering pattern image was selected, in order to still retain high-frequency scattering information in the image data. After cropping, the camera images were resized to 100 × 100 pixels and converted to grayscale. Before the images were sent to the NN, each individual image was normalized to have a mean of 0 and a standard deviation of 1. The NN was formed of two convolutional layers, followed by a max pooling, dropout, and fully connected layer, with a regression output. In the case of the mixture determination, the NN had two outputs, corresponding to the concentration of 5 μm diameter silicon dioxide microparticles and 8 μm diameter melamine resin microparticles. For the salinity measurements, the NN had a single output, corresponding to the ppt of salinity.

The input layer (grayscale cropped scattering pattern image of 100 × 100 pixels) was followed by two stages of convolutional then max pooling layers, whereby the convolutional layers had 64 filters with a kernel of 3 × 3 and stride of 1, and the max pooling layers had a kernel of size 2 × 2 and stride of 3 [70]. A dropout rate of 50% was used [71], leading to a fully connected layer of 512 neurons and weight decay of 0.0005 [70]. The learning rate of the NNs was 0.0001, while an adaptive moment estimation optimiser [72] was used to minimise mean square error cost function for regression. Through trial and error, the entire architecture was optimised so that the memory requirement of the NN was appropriate to be executed on a Raspberry Pi.
2. Results and discussion

2.1. Identification of microparticle mixture concentration

The NN was designed to produce two numerical outputs from the scattering pattern input, corresponding to the concentration percentage for 5 μm silicon dioxide and 8 μm melamine resin microparticles. The two outputs were independent of each other, and hence could be used to provide absolute concentration values. Figure 3 shows the results for a series of measurements of different mixtures, showing the output for a) 5 μm silicon dioxide and b) 8 μm melamine resin microparticles, from a mixture of these particles in a solution. Each data point on the figure, which shows the mean and standard deviation, corresponds to the prediction from 10 scattering patterns. The R-squared value for the silicon dioxide data is 0.9902 and the R-squared value for the melamine resin data is 0.9978.

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Figure 2. Schematic of the application of the NN for microparticle sensing.

Figure 3. Prediction accuracy for the simultaneous identification of the absolute concentration of (a) 5 μm silicon dioxide and (b) 8 μm melamine resin microparticles, from a mixture of these particles in a solution. Each data point on the figure, which shows the mean and standard deviation, corresponds to the prediction from 10 scattering patterns. The R-squared value for the silicon dioxide data is 0.9902 and the R-squared value for the melamine resin data is 0.9978.
which could be achieved by physically taking more measurements, or artificially, via augmentation [73]. Whilst
the particle concentrations in this proof-of-principle demonstration are higher than might be expected in the
marine environment [74] owing to the need for sufficient signal collection, our previous work [61] has shown
the capability for the identification of single particles using an alternative experimental setup.

2.2. Salinity identification
As the concentration of salt in a solution increases from 0 ppt to 100 ppt, a change in the refractive index of the
water occurs in which the microparticles are present. For example, at a wavelength of 589.3 nm, the refractive
index ranges from 1.334 (0 ppt) to 1.343 (50 ppt) and 1.352 (100 ppt) [75]. Such a change in the refractive index
therefore causes a change in the scattering pattern produced by the microparticles. Here, a NN was trained on
salinity values of 0 ppt, in steps of 10 ppt, up to 100 ppt, with 10 scattering patterns recorded for each salinity. The
NN was then trained for 100 epochs. Subsequently, the NN was trialled on a range of other salinities that
 corresponded to known values of water bodies, such as the Baltic Sea (8 ppt) and average sea water (35 ppt),
which were predicted with mean values and standard deviation of 8.06 ± 1.67 ppt and 34.24 ± 4.03 ppt,
respectively (see figure 4). Each data point on the figure corresponds to 10 recorded scattering patterns. The
accuracy of the salinity measurements clearly shows the capability of the NN approach for detecting very subtle
changes in the scattering patterns.

3. Conclusions
In conclusion, we have shown the simultaneous identification of absolute concentration percentage of 5 µm
silicon dioxide and 8 µm melamine resin microparticles, when the particles were present in water. Additionally,
we have demonstrated the identification via a NN of salt concentration of water containing 8 µm melamine resin
microparticles, for salinities including agriculture irrigation and average sea levels. By running the NN on a
Raspberry Pi, we have shown the potential for a portable and low-cost marine environmental sensor. Since the
scattering pattern from particles varies depending on the size and material, this proof-of-principle technique,
which involves using an NN to classify concentrations of two materials of different sizes and refractive index,
could be extended to particles of other sizes and materials, such as polystyrene and polyethylene.

Figure 4. Prediction accuracy of the NN for identification of salinity directly from the scattered light, showing the mean and standard
deviation in the prediction. The R-squared value for the data is 0.999. Values of salinity taken from [76–81].
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References

[1] Eriksson M, Lebreton I C M, Carson H S, Thiel M, Moore C J, Borrerro C, Galgani F, Ryan P G and Reisser J 2014 Plastic pollution in the world’s oceans: more than 5 trillion plastic pieces weighing over 250,000 tons afloat at sea PLoS One 9 e1111913
[2] Rochman C M, Kross S M, Armstrong J B, Bogan M T, Darling E S, Green S J, Smyth A R and Vetsimis D 2015 Scientific evidence supports a ban on microbeads Environ. Sci. Technol. 49 10759–61
[3] Napper I E, Bakir A, Rowland S J and Thompson R C 2015 Characterisation, quantity and sorptive properties of microplastics extracted from cosmetics Mar. Pollut. Bull. 99 178–85
[4] Cheung P K and Fok L 2016 Evidence of microbeads from personal care product contaminating the sea Mar. Pollut. Bull. 109 582–5
[5] Arthur C, Baker J and Bamford H 2009 Proc. of the Int. Research Workshop on the Occurrence, Effects, and Fate of Microplastic Marine Debris (NOAA, September 11–12, 2008) Technical Memorandum NOS-OR&R-30
[6] Costa M F, Do Sul A I, Silva-Cavalcanti J S, Araújo M C B, Spengler A and Tourinho P S 2010 On the importance of size of plastic fragments and pellets on the starvation: a snapshot of a Brazilian beach Environ. Monit. Assess. 168 299–304
[7] Côas A et al 2014 Plastic debris in the open ocean Proc. Natl. Acad. Sci. 111 10239–44
[8] Cole M, Lindquepe P, Fileman E, Halbans C, Goodhead R, Moger J and Galloway T S 2013 Microplastic ingestion by zooplankton Environ. Sci. Technol. 47 6646–55
[9] Andrady A L 2011 Microplastics in the marine environment Mar. Pollut. Bull. 62 1596–605
[10] Setälä O, Fleming-Lehtinen V and Lehtiniemi M 2014 Ingestion and transfer of microplastics in the planktonic food web Environ. Pollut. 185 77–83
[11] Rummel C D, Lóder M G J, Fricke N F, Lang T, Griebeler E-M, Janke M and Gerdts G 2016 Plastic ingestion by pelagic and demersal fish from the North Sea and Baltic Sea Mar. Pollut. Bull. 102 134–41
[12] Tanaka K and Takada H 2016 Microplastic fragments and microbeads in digestive tracts of planktivorous fish from urban coastal waters Sci. Rep. 6 34351
[13] Van Cauwenbergh L, Claessens M, Vandegheucke M B and Janssen C R 2015 Microplastics are taken up by mussels (Mytilus edulis) and lugworms (Arenicola marina) living in natural habitats Environ. Pollut. 199 10–7
[14] Sussarellu R, Suquet M, Thomas Y, Lambert C, Fabioux C, Eve M and Pernet J 2016 Oyster reproduction is affected by exposure to polystyrene microplastics 113 2430–3
[15] Lee K-W, Shim W J, Kwon O Y and Kang J-H 2013 Size-dependent effects of micro polystyrene particles in the marine copepod Tigriopus japonicus Environ. Sci. Technol. 47 11278–83
[16] Cole M, Lindquepe P, Fileman E, Halbans C and Galloway T S 2015 The impact of polystyrene microplastics on feeding, function and fecundity in the marine copepod Calanus helgolandicus Environ. Sci. Technol. 49 1130–7
[17] Iñiguez M E, Conesa J A and Fullana A 2017 Microplastics in spanish table salt Sci. Rep. 7 8620
[18] Yang D, Shi H, Li L, Li J, Jabeen K and Kolandhasamy P 2015 Microplastic pollution in table salts from China Environ. Sci. Technol. 49 13622–7
[19] Mason S A, Welch V G and Neratko J 2018 Synthetic Polymer Contamination in Bottled Water Frontiers in Chemistry 6 407
[20] Bouwmeester H, Hollman P C H and Peters R J B 2015 Potential health impact of environmentally released micro- and nanoparticles in the human food production chain: experiences from nanotoxicology Environ. Sci. Technol. 49 8932–47
[21] Rist S, Almroth B C, Hartmann N B and Karlsson T M 2018 A critical perspective on early communications concerning human health aspects of microplastics Sci. Total Environ. 626 720–6
[22] Brown D M, Wilson M R, MacNee W and Donaldson K 2001 Size-dependent proinflammatory effects of ultrafine particles: a role for surface area and oxidative stress in the enhanced activity of ultratines Toxicol. Appl. Pharmacol. 175 191–9
[23] Bernsten P, Park C Y, Tsuda A et al 2010 Biomechanical effects of environmental and engineered particles on human airway smooth muscle cells Journal of the Royal Society Interface 7 331–40
[24] Ryan P G, Moore C J, van Franeker J A and Moloney C L 2009 Monitoring the abundance of plastic debris in the marine environment Philos. Trans. R. Soc. B Biol. Sci. 364 1999–2012
[25] Van Cauwenbergh L, Vanreusel A, Mees J and Janssen C R 2013 Microplastic pollution in deep-sea sediments Environ. Pollut. 182 495–9
Kaidarova A, Marengo M, Marinaro G, Geraldi N, Duarte C M and Kosel J 2018 Flexible and biofouling independent salinity sensor

Nelms S E, Galloway T S, Godley B J, Jarvis D S and Lindeque P K 2018 Investigating microplastic trophic transfer in marine top predators

Lee S-H, Roichman Y, Yi G-R, Kim S-H, Yang S-M, Van Blaaderen A, Van Oostrum P and Grier D G 2007 Characterizing and tracking colloidal clusters with video holographic microscopy

Ulanowski Z, Wang Z, Kaye P H and Ludlow I K 1998 Application of neural networks to the inverse light scattering problem for spheres

Wang C, Cheong F C, Ruffner D B, Zhong X, Ward M D and Grier D G 2016 Holographic characterization of contaminants in water: differentiation of suspended particles in heterogeneous dispersions

Bohren C F and Huffman D R 2008 Absorption and Scattering of Light by Small Particles (New York: Wiley)

Mills B et al 2008 Direct measurement of the complex refractive index in the extreme ultraviolet spectral region using diffraction from a nanoparticle array

Lee S-H, Roichman Y, Yi G-R, Kim S-H, Yang S-M, Van Blaaderen A, Van Oostrum P and Grier D G 2007 Characterizing and tracking single colloidal particles with video holographic microscopy

Gasperi J, Dirs R, Bonin T, Rocher V and Tassin B 2014 Assessment of floating plastic debris in surface water along the Seine River

Philips L A, Ruffner D B, Cheong F C, Blusewicz J M, Kasimpegu B, Waisi B, McCutcheon J R and Grier D G 2017 Holographic characterization of contaminants in water: differentiation of suspended particles in heterogeneous dispersions

Roweley H A, Baluja S and Kanade T 1998 Neural network-based face detection

Hinton G E and Salakhutdinov R R 2006 Reducing the dimensionality of data with neural networks

Mills B, Heath D J, Grant-Jacob J A, Xie Y and Eason R W 2018 Image-based monitoring of femtosecond laser machining via a neural network

Gasperi J, Dirs R, Bonin T, Rocher V and Tassin B 2014 Assessment of floating plastic debris in surface water along the Seine River

Environ. Res. Commun. 5 (2019) 035001
[66] Pawluczicz P, McDougall T J, Feistel R and Tailleux R 2012 An historical perspective on the development of the thermodynamic equation of seawater-2010 Ocean Sci. 8 161–74

[67] Heath D J, Grant-Jacob J A, Xie Y, Mackay B S, Baker J A G, Eason R W and Mills B 2018 Machine learning for 3D simulated visualization of laser machining Opt. Express 26 4984–8

[68] Specht D F 1991 A general regression neural network IEEE Trans. neural networks 2 568–76

[69] Abadi M et al 2016 Tensorflow: a system for large-scale machine learning OSDI 16 265–83

[70] Krizhevsky A, Sutskever I and Hinton G E 2017 Imagenet classification with deep convolutional neural networks Communications of The ACM 60 84–90

[71] Srivastava N, Hinton G, Krizhevsky A, Sutskever I and Salakhutdinov R 2014 Dropout: a simple way to prevent neural networks from overfitting J. Mach. Learn. Res. 15 1929–58

[72] Kingma D P and Ba J 2014 Adam: a method for stochastic optimization arXiv Prepr. arXiv 1412.6980

[73] Perez I and Wang J 2017 The effectiveness of data augmentation in image classification using deep learning arXiv Prepr. arXiv 1712.04621

[74] Bergmann M, Wirzberger V, Krumpen T, Lorenz C, Primpke S, Tekman M B and Gerdts G 2017 High Quantities of Microplastic in Arctic Deep-Sea Sediments from the HAUSGARTEN Observatory Environ. Sci. Technol. 51 11000–10

[75] Tan C-Y and Huang Y-X 2015 Dependence of refractive index on concentration and temperature in electrolyte solution, polar solution, nonpolar solution, and protein solution J. Chem. Eng. Data 60 2827–33

[76] Nissling A 1994 Survival of eggs and yolk-sac larvae of Baltic cod (Gadus morhua L.) at low oxygen levels in different salinities ICES Marine Science Symposium 198 626–31

[77] Mudie P J, Aksu A E and Yasar D 2001 Late quaternary dinoflagellate cysts from the black, Marmara and Aegean seas: variations in assemblages, morphology and paleosalinity Mar. Micropaleontol. 43 155–78

[78] Agh N, Abatzopoulos T J, Kappas I, Van Stappen G, Razavi Rouhani S M and Sorgeloos P 2007 Coexistence of sexual and parthenogenetic artemia populations in lake urmia and neighbouring lagoons Int. Rev. Hydrobiol. 92 48–60

[79] Burkholder D A, Fourqurean J W and Heithaus M R 2013 Spatial pattern in seagrass stoichiometry indicates both N-limited and P-limited regions of an iconic P-limited subtropical bay Mar. Ecol. Prog. Ser. 472 101–15

[80] Glenn E P, Brown J J and O’Leary J W 1998 Irrigating crops with seawater Sci. Am. 279 76–81

[81] Rahman T, Mirza A T M, Rahman S H and Majumder R K 2012 Groundwater quality for irrigation of deep aquifer in southwestern zone of Banglades Songklanakarin J. Sci. Technol. 34 345–52