Recognition and measurement of dispersed oil droplets in a water column

Identification et mesure de gouttelettes d'huile dans une colonne d'eau

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ABSTRACT
A non-intrusive method, based on laser-sheet illuminated imagery and image processing techniques, was used to explore the phenomena of natural dispersion of oil in a water column. The method was used in a laboratory experiment to determine the distribution of oil droplets in the water column. The findings of this study suggest that this approach is a fast and accurate way to sample oil droplets in a water column without disturbing the flow.

RÉSUMÉ
Une méthode non intrusive, basée sur l'imagerie laser et les techniques de traitement d'images, a été utilisée pour explorer la dispersion naturelle d'huile dans une colonne d'eau. La méthode mise en œuvre dans une expérience de laboratoire, a servi à déterminer la distribution des gouttelettes d'huile dans la colonne d'eau. Les résultats de cette étude suggèrent que cette approche constitue un moyen rapide et fiable pour échantillonner les gouttelettes d'huile dans une colonne d'eau sans perturber l'écoulement.

Introduction

Natural dispersion of surface oil slick is defined as the breaking up of the coherent oil slicks into droplets, and the spreading and diffusion of these droplets in the water column (ASCE Task committee, 1997). From the point of view of pollution control, it is highly desirable to understand the mechanisms leading to the dispersion of oil and above all, to have a method that can be used to readily estimate the quantity of dispersed oil in the water column. Over the last two decades, vast improvement has been introduced in the methods used to investigate the dispersion of oil in water, both in the laboratory experiments and field observations. Forrester (1971) manually counted oil droplet of various sizes under a microscope. Lunel (1993) conducted direct measurement of oil droplets in the sea using the laser Phase Doppler Particle Analyser. Delvigne and Sweeney (1988) performed extensive laboratory experiments to investigate the natural dispersion of oil. In their work, the dispersed oil droplets were sampled and kept to stand in a vertical position for 20 hours. The larger droplets ($d_o \geq 100\ \mu m$) were counted from photographs, while the smaller droplets ($d_o \leq 100\ \mu m$) were measured and counted under a microscope.

Strictly speaking, all the sampling procedures reported disturb the droplet size distribution in the water column. The writers propose to measure the droplet distribution using a non-intrusive method, that is, through capturing digital image of the water column. The distribution of the small droplets in the column is determined using digital image analysis technique that has been developed in other fields of applied sciences, such as those dealing with bitmaps, image recognition and granulometry.

Greyscale Bitmap

A *bitmap* can be visualised as an image that comprises individual square cells called pixels, with each pixel having a specific colour (or grey value). Bitmaps are graphic images in their pixel-by-pixel form, and are always rectangular. In many applications, it is a lot more useful to represent bitmaps as greyscale images, the digital equivalent of black-and white photographs. For practical purpose, 256 levels of grey are sufficient to represent a realistic greyscale image. Each pixel in the image is represented by a number from 0 through to 255.

Digital Image Granulometry

As originally conceived for binary images (Matheron, 1967), *granulometries* are employed to characterise the size distribution and shape information of granules in an image. The notion of a granulometry, as conceived by Matheron, has to do with the process of sieving in terms of fitting. Practically, the most useful granulometry is structured on openings (or closings) with the homothetics of a simple convex structure element. The structure element can be a line, a square, or a hexagon, and are referred to as ''linear granulometry'', ''square granulometry'', or ''hexagonal granulometry'', respectively. If an image is considered as a collection of granules, then whether or not an individual granule will pass through a sieve depends on its size and shape relative to the mesh of the sieve. By increasing the mesh size while keeping the basic shape, more granules within the image will pass through the sieve. Eventually, all granules will pass through the sieve, when the mesh size is just bigger than the largest object in the field. Therefore one can derive the mesh-size or the equivalent granule-size distribution for the granules within the domain. This

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approach is similar to the use of the term ‘‘%-passing’’ in particle size distribution.

One way to proceed is to use the digitisation methodology, which is in accordance to a typical grid-type approximation employed in other areas of mathematical analysis. The concept is built upon the representation of an image by a bound matrix whereby a xy-plane is partitioned into square regions, with each square centred at a lattice point (i, j), where i and j are in the set of Z of integers. A square with its centre located at a lattice point is called a pixel. A digital image is obtained by assigning an integer number, called a grey value, to each pixel in some collection of pixels. Very often, the domain of a digital image is rectangular in shape and contains a finite number of pixels. The digital image will be represented in a manner similar to a matrix or a two-dimensional array, with a grey value for each pixel specified by a row index (j) and a column index (i) within the array. Vincent (1994) proposed a class of fast greyscale granulometry algorithm with an ‘‘opening tree’’ in which a greyscale image is represented by the successive openings by line segments of increasing size.

However, these methods do not recognise the shapes or regularity of the granules. As a result, two difficulties arise:

1. the lack of shape-definition, or in image processing term, an appropriate notion of convexity; and
2. the lack of characteristic-definition of similar objects of various sizes, i.e. there is no applicable scale multiplication factors by which one can defines granules of a certain size to that of another, (Dougherty 1992).

These difficulties cannot be resolved completely. However, they are not serious obstacles to the application in oil droplets, which are essentially spherical in shapes, both ‘‘convex’’ and ‘‘scaleable’’.

Experimental Methodology

In this study, a non-intrusive approach to measure dispersed oil droplets in a water column has been developed. The method of measurement is similar to that of particle-image-velocimetry, except that the captured images are analysed differently using different techniques and criteria, which impose a set of exacting constraints for acquisition and analysis of the images.

Acquisition of Oil-droplet Image

The laser imagery technique requires an illuminated plane and an image-capturing device. In this study, the target plane in a water column was illuminated using a laser sheet generated using a 5W argon-ion laser. The laser was operated in continuous mode but could be pulsed by using a beam chopper. The illuminated target plane is captured on film using a Nikon camera fitted with a 100-300 mm macro lens and micro lens attachments. Figure 1 shows a schematic sketch of the configuration of the system.

In this study, a magnetic stirrer was used to generate a flow field that broke up the surface oil slick and entrained it into the water column. The target plane was arranged to coincide with a suitable circumferential plane where the flow vectors were generally in the same illuminated plane. The typical flow speed in the target

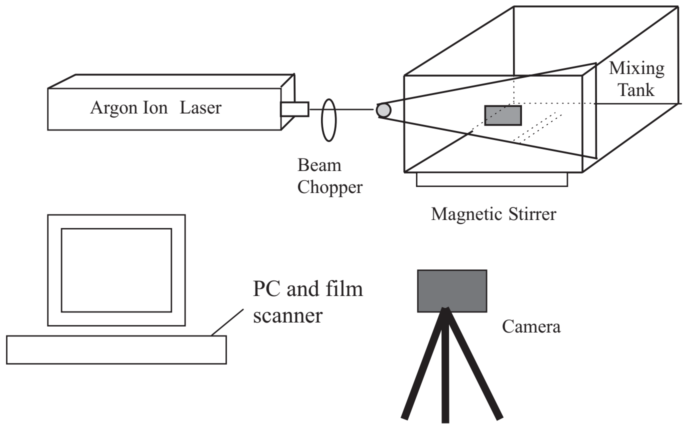


Fig. 1. A schematic sketch of the experimental setup.

area was about 0.05 m/s.

Using a magnetic stirrer was a quick and convenient way of setting up a flow field. However, the turbulence flow field would not be well defined. However, the objective of this study was to develop the techniques to capture oil-droplet distribution, both the size and number of droplets. Hence the role of the hydrodynamics was secondary. We recognise the need for proper control of the turbulence field and this would be addressed in the follow-up work that would correlate the turbulence intensity and the characteristics of oil entrainment in a water column.

The captured image was digitised and analysed using an IBM-compatible PC. As such, the size of the image and its resolution was constrained by the processing capacity of the PC. Perhaps the more important considerations were the relative size of the objects, the concentration and speed of the droplets in the flow field. Our considerations focused on the practical size of the bitmap, the size of the target area and the speed of droplet limit the resolution of the pixel. The appropriate conditions for capturing the image were established after defining the achievable resolution and objectives. Firstly, as the image processing would be carried out using an IBM-compatible PC, a bitmap image of 1000x1000 pixels was decided upon. This size was reasonably big and yet not too demanding on the processing capability of a PC to achieve a reasonable turnaround time.

Oil droplets in a water column are usually sub-millimetre in size, typically ranging from about 10 µm to 200 µm. The median size has been reported to be about 70 µm. Our experience shows that, in order not to swarm the image, the target area should have a small concentration of objects with the largest image object of a dimension of about 5~10% of the smaller dimension of the image window. Therefore for a window width of 1000 pixels, 5% of the length would be 50 pixels and corresponded to 200 µm. Therefore, the resolution of a pixel would be 4µm. In this case, the definition of the smallest droplets would be adequate, since it would take at least 2 pixels to map the diameter of the smallest droplets of 10µm. However, it would mean that the target area would be 4 mm by 4 mm. By using a combination of macro and micro lenses, we managed to map the target area on film at a magnification factor of 2.5, an area of 10 mm by 10 mm on the photographic film.

A 35 mm film measures 35 mm by 25 mm. As such, the domain in the flow field that was captured on film is 17.5 mm by 12.5 mm. The light intensity would be low, and to capture a clear image, we have to resort to high laser illumination and fast-acting film. In our case, we used films with ISO ratings of 1000 to 6400. The third constraint was the movement of the oil-droplet. Because of the resolution of the image, (1 pixel = 4 µm) the movement had to be slow or the light pulse/exposure duration had to be short. Any displacement of more than 4µm would distort the object in the image. Knowing that the oil droplets move at 0.05 m/s then the exposure duration had to be less than 4µm /0.05 m/s or 1/12500 s. This exposure duration was achieved with a combination of high camera shutter speed and pulsing the laser illumination. In this study, the laser was pulsed to produce 1/12500 s burst and the camera shutter speed was set to 1/8000s, slightly less than twice the exposure duration. As a result, the camera always captured a single burst of light in the image.

With the above considerations, the target sampling area of an image on the film, when set to 1000×1000 pixels corresponded to an area of 10 mm by 10 mm on the film or 4 mm by 4 mm of the flow field. A single frame on a 35 mm film (35 mm by 25 mm) would therefore contain 3 by 2 or 6 such images. In this study, the analysis was always carried out using several images obtained from the same frame of the film.

Digitisation and Pre-processing of Images

A film scanner (Nikon 35 mm Film Scanner LS-1000) was used to digitise the image captured on film to obtain a 256 grey scale image. In this study a 10×10 mm (corresponding to 4×4 mm in the actual dimension at a magnification of 2.5) was digitised at a spatial resolution of 4 µm/pixel to obtain a digital image of 1000×1000 pixels.

During the scanning process, we opted for pre-processing by setting the "black-point" and "white point" as a means to filter and enhance the image, respectively. The "black point" represents the 'desired' darkest point in the image for the specified grey level, whilst the "white point" corresponds to the desired or threshold of brightness in the image. Setting the black point resulted in filtering the noise from the black background that might be of the result of non-uniform illumination. During the pre-processing, all the pixels darker than the black point was set to the minimum (greyscale value=0), thus improving the quality of the image under analysis. The "white point" was used to enhance the oil droplet images. All the pixels brighter than the white point will be set to the maximum (greyscale value=255). Figures 2(a) and 2(b) show the same image before and after pre-processing. Substantial improvement in the quality and contrast of the image is evidenced.

Theoretically, one needs only either the 'black' or 'white' point to segregate the objects from the background. However, the use of both provides an avenue to eliminate dimmer objects that are not in the plane of illumination.

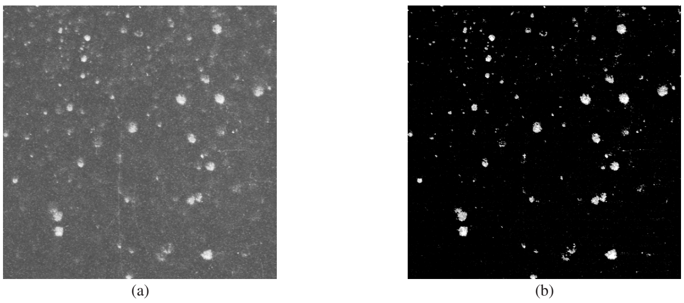


Fig. 2. An image of oil droplets in a water column (a) before and (b) after the pre-processing during the scanning process.

Oil droplet Recognition and Measurement

In this study, oil droplets form the square structure elements. Elements with uniform pixel value above the grey level threshold were used to map the digital greyscale image sequentially. After the whole sequence of mapping, the number of the oil droplets fallen into various size classes were then counted.

A square structure element $S(k)_{i,j}$ with a length of k is a collection of pixels or a k×k matrix on a 2-dimensional plane. Subscripts i and j are the upper-left lattice indices of pixel I(i, j), representing its position within the bound matrix of a greyscale digital image.

Conventionally, the origin of the bound matrix of a digital image is located at its up-left corner. Therefore, by the above definition, the four neighbouring pixels of a target square structure element are: I(i-1, j-1), I(i+k, j-1), I(i-1, j+k), and I(i+k, j+k). See the sketch in Fig. 3. It follows that a square segment of pixels with length k in the digital image bound matrix is one that all the pixels within the square segment have the grey levels greater than or equal the threshold value while the grey levels of its four neighbouring pixels, I(i-1, j-1), I(i+k, j-1), I(i-1, j+k), and I(i+k, j+k), are under the threshold value. This is the criterion used in the recognition of an object, and subsequent determination of the size of this object.

Based on these two definitions, the algorithm for oil droplet recognition and measurement has been developed and shown in Fig. 4. The algorithm is as follow:

1. First, a range of suitable square structure elements with decreasing size was selected. The largest, k_{max} and smallest size, k_{min}, were selected before hand. The size of the structure element is analogous to the size of the mesh of a sieve. An array is initialised to store the number of droplets in each size range.

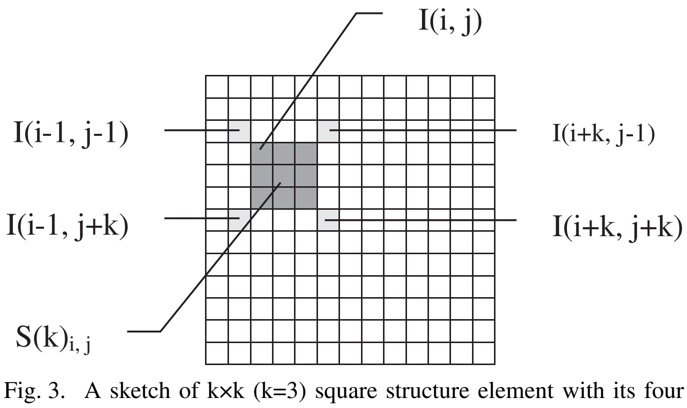


Fig. 3. A sketch of k×k (k=3) square structure element with its four neighbouring pixels in the bound matrix

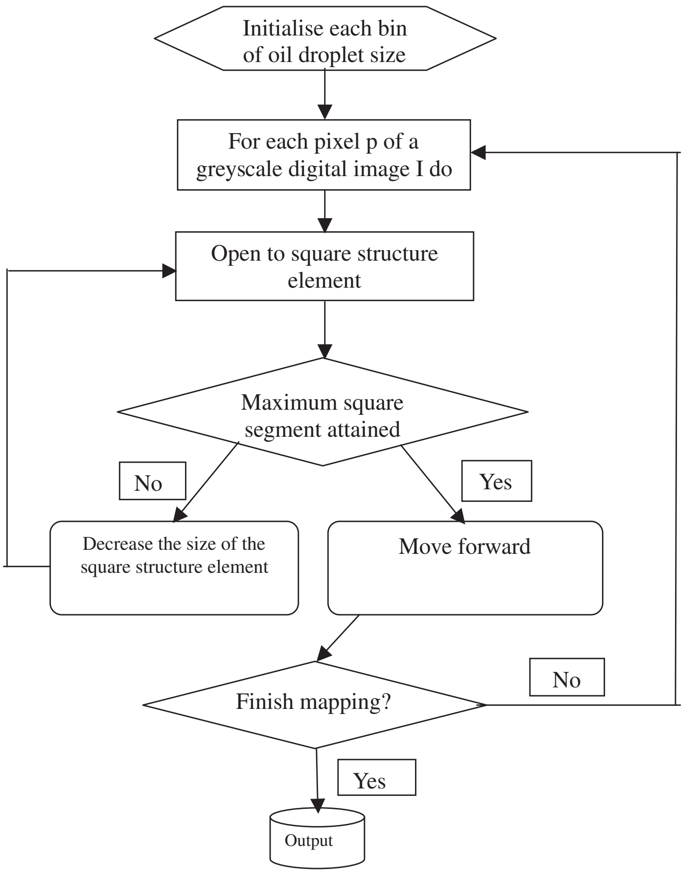


Fig. 4. Flowchart of the algorithm for oil droplets recognition and measurement

2. A suitable greyscale value that would register as a structure element is then selected.
3. Then a pointer is swept from left to right, row by row, to identify the top left corner of a structure element. Identification is positive when the greyscale value of the pixel encountered corresponds to that of a structure element, in this case, ‘‘white’’. Upon detecting such an element, the size-fitting process is activated.
4. The size fitting process begins by assigning this pixel as I(i,j). Then a bound square elements of k by k pixels is generated, with I(i,j) as the top left corner. The process begins with $k=k_{max}$.
5. The greyscale values of all the pixels in the bound elements are determined. To fit the criterion, all the pixels in the square element have to be ‘‘white’’ and the four corners, ‘‘non-white’’.
6. If the criterion is not satisfied, then the next smaller bound structure element is generated. Usually this corresponds to a value of k that is one unit smaller than before. Obviously, the smallest possible will be that of k_{min} pixels. Then steps (5) and (6) are repeated until the criterion is satisfied.
7. If the criterion is satisfied, then the size of the droplet is set equal to k, and the pointer in the droplet size array of the corresponding entry is increased by one. Then all the pixels in the bound structure element are assigned a greyscale value corresponding to non-structure element, i.e. black in this case. This is a necessary process to avoid double counting.
8. The process is completed when the last pixel at the bottom right corner is reached.

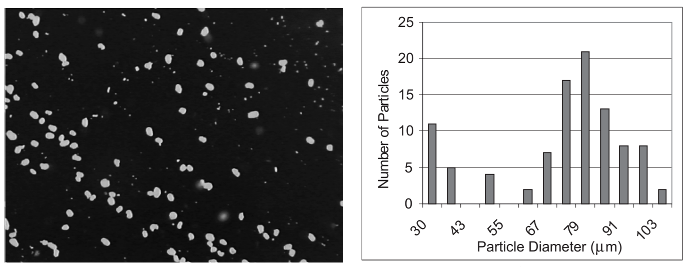
This method of computation would not be able to recognise non-convex and/or elongated objects, and objects outside the range of k_{max} and k_{min}. However, the method works with adjacent objects most of the time. The usual failings of overlapping and partially covered objects could be reduced but not eliminated.

Calibration

A programme was developed based on the above algorithm. The performance of the programme was tested and verified using artificially generated images of perfectly shaped convex objects of known sizes. The performance was found to be excellent.
Then, images of elliptic seeding particles (manufacturer's specification - mean diameters 85μm) were captured (Fig. 5(a)) and analysed using the programme. Figure 5(b) shows the measured particle size distribution. The mean diameter of the objects, as indicated in Fig. 5(b) was about 71μm and the median diameter was 86μm. Further analysis showed that the image noise and the split particles near the image border caused over-counting of the smaller particles. Consequently the algorithm produced a smaller particle mean diameter and an artificial second object group of much lower diameters. By elimination this smaller diameter group, the estimated mean diameter became 85 μm and the median diameter remained at 86 μm. The calibration results render confidence that the algorithm can be used to recognise and determine the size and distribution of oil-droplets in a water column.

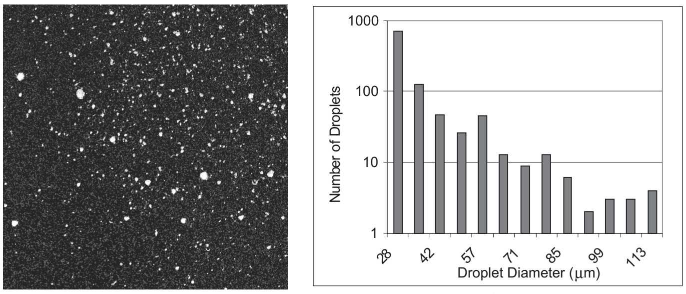
Oil Droplets Recognition and Measurement

Figure 6(a) shows a typical digitised image of oil droplets in a water column. The droplet size distribution was computed using the algorithm described. The statistical size distribution obtained from five droplet images is shown in Fig. 6(b). The maximum diameter of the dispersed oil droplets is 113 μm. Ninety-eight percent oil droplets are less than 78 μm.
Figure 7 shows the cumulative frequency distribution of oil droplets in the water column in this study and two sea trials (Lunel, 1993). The comparison shows good agreement.



(a) (b)

Fig. 5. (a) Image of the seeding particles in a water column, and (b) the particle size distribution as obtained using the proposed algorithm.



(a) (b)

Fig. 6. (a) A typical oil droplet image in the experiment (5mm×5mm), and (b) the droplets size distribution

Conclusion

A non-intrusive experimental method used to measure the dispersed oil droplet in a water column has been presented. The method is based on laser imagery and digital image processing and recognition techniques. The findings of this study shows that the algorithm based on granulometry with maximum square openings can be used to recognise and determine the size of the dispersed oil droplets at an acceptable accuracy. The distribution as determined using a laboratory experiment of oil dispersion in a water column produced similar results to that of the field measurements conducted by Lunel (1993).

Notation

i, j	lattice indices of pixel in bound matrix
k	length of a square structure element
I(i, j)	the pixel at the ith column and jth row.
$S(k)_{i,j}$	k×k square structure element

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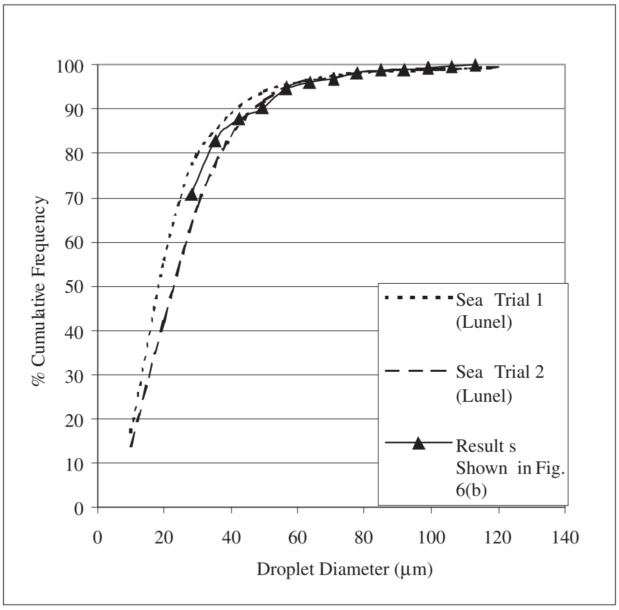

Fig. 7. A comparison of the droplet-size distribution of this study and that of the field data by Lunel (1993).

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