An integrative image measurement technique for dense bubbly flows with a wide size distribution

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Abstract

The measurements of bubble size distribution are ubiquitous in many industrial applications in chemical engineering. The conventional methods using image analysis to measure bubble size are limited in their robustness and applicability in highly turbulent bubbly flows. These flows usually impose significant challenges for image processing such as a wide range of bubble size distribution, spatial and temporal inhomogeneity of image background including in-focus and out-of-focus bubbles, as well as the excessive presence of bubble clusters. This article introduces a multi-level image analysis approach to detect a wide size range of bubbles and resolve bubble clusters from images obtained in a turbulent bubbly wake of a ventilated hydrofoil. The proposed approach was implemented to derive bubble size and air ventilation rate from the synthetic images and the experiments, respectively. The results show a great promise in its applicability for online monitoring of bubbly flows in a number of industrial applications.

Keywords: Image analysis, Bubbly flow, Bubble size distribution, Shadow image velocimetry, Ventilated hydrofoil wake, Synthetic bubble images.

1. Introduction

Bubbly flows occur frequently in natural systems and are also used for different applications in petroleum, energy-producing and chemical industries. Some of the common applications involve bubble columns which are used as reactors in a variety of chemical and biochemical processes, e.g. the Fischer-Tropsch process for hydrocarbon synthesis, hydrogenation of unsaturated oil, coal liquefaction, fermentation, waste water treatment etc (Smith et al., 1996; Lau et al., 2013). Bubbly flows are also ubiquitously found in flotation cells (Sadr-kazemi and Cilliers, 1997), aeration studies (Roesler and Lefebvre, 1989) and spargers (Geary and Rice, 1991) etc. In many of such processes, the accurate prediction of pressure drop and wall heat transfer is necessary, both of which are strongly dependent upon the concentration, spatial distribution and morphology of the bubbles (Kamp et al., 2001). Similarly, in many liquid-gas systems, gases are dispersed in liquids to obtain large interfacial area available for chemical reactions, heat and mass transfer processes. The rate of such processes is characterized by bubble surface area flux which is closely associated with the bubble size distribution (Junker, 2006).

Different techniques have been employed to measure bubble size distributions. Broadly, it can be divided into two categories – intrusive and non-intrusive techniques. Both these methods have been extensively reported in the literature – some of the intrusive methods employ capillary suction probes (Laakkonen et al., 2005), conductivity probes (Liu and Bankoff, 1993), optical fiber probes (Saber et al., 1995) and wire-mesh sensors (Prasser, 2008), etc. The non-intrusive methods include interferometric particle imaging (Glover et al., 1995), , laser Doppler velocimetry (Mudde et al., 1998) , extinction and scattering activity measurement (Zaidi, 1998), phase Doppler anemometry (Laakkonen et al., 2005) and other particle-imaging techniques

(Tayali and Bates, 1990; Adrian, 1991; Grant, 1997), etc. In general, non-intrusive methods are preferred over intrusive methods which disturb the local flow fields because of the placement of the probes.

Digital image analysis offers many advantages in terms of flexibility, relative insensitivity to the optical properties of the dispersed phase, easier optics alignment as compared to laser-diffraction methods, as well as the capability of providing the velocity and size information of the dispersed phase simultaneously. Thus, it is very convenient and time efficient for online monitoring and analysis of a large number of images. However, to implement this technique for real-time analysis of the bubbly flow images from different engineering applications pose multifarious challenges. These challenges include, for instance, the computational speed for real-time image processing, the ability to cope with the poor quality of images caused by varying intensity characteristics of the background and out-of-focus objects, and the robustness of the technique especially in its capability to resolve overlapped clusters in the high void-fraction flows.

The optical image analysis have been used recently for quantifying the bubble size distribution (e.g. Honkanen et al., 2010; Ferreira et al., 2012; do Amaral et al., 2013; Kracht et al., 2013; Lau et al., 2013). Generally, due to the excessive coalescence and break-up of bubbles, most of the proposed techniques for bubble image processing produce considerable errors when applied to flows with high superficial gas and liquid velocities. These errors are closely related to the challenge of extracting accurate bubble information from large clusters due to the coalescence of bubbles. A brief review of these techniques will be presented in section 3.1. Overall, these techniques are still limited in their robustness to resolve large bubble clusters particularly under highly unsteady flows with large void fractions of bubbles. Another limitation of the reported techniques is related to their ability to deal with a wide range of bubble size distribution. In

addition, algorithms with significant improvements in computational speed are needed for fast processing of a large number of images and online monitoring of bubble concentration and distribution.

Thus, in the present study, we introduce an integrative image measurement technique to analyze high void fraction bubbly flows with a wide dynamic size range of bubble size. The development of this technique is driven by our recent study on the bubbly wake flows of aerated hydrofoils. This research is focused on developing a test-bed through conducting physical water-tunnel experiments to quantify the dissolved oxygen transfer across bubbles under various flow conditions. The experiments result in a large quantity of varying quality of bubble images with significant clustering due to highly unsteady and complex flows and coalescence of bubbles. These images make it unfeasible to implement prior measurement techniques to achieve fast and accurate image analysis.

This paper is structured as follows: Section 2 provides the details for the experimental facility, setup and the optical approach used to capture digital images. The proposed image analysis algorithm is described in Section 3. Subsequently in Section 4, we present validation of our image analysis technique through both simulation and experimental approaches, which is followed by a final conclusion in Section 5.

2. Description of experimental setup

The experiments were conducted in the high-speed water tunnel at Saint Anthony Falls Laboratory (SAFL) of the University of Minnesota. The tunnel has a horizontal test section of 1 m (Length) $\times$ 0.19 m (Width) $\times$ 0.19 m (Height) with three sides having plexiglass wall for optical access. The tunnel is designed for cavitation and air ventilation studies and is capable of

operating with velocity in excess of 20 m/s. A special design feature of the tunnel provides for fast removal of large quantities of air bubbles generated during cavitation and ventilation experiments, allowing us to conduct bubbly flow experiments for extended periods of time with little effect on test section conditions.

During the experiments, a NACA0015 hydrofoil was installed in the test section with angle of attack (α) of 0° , 4° and 8° . The hydrofoil was 190 mm in span and 81 mm in chord. As shown in Figure 1, a narrow spanwise slot allows air to be injected into the flow over the hydrofoil. The full width of the injection slot is used for measurements of oxygen uptake. This results in a dense spanwise bubbly wake. However, in order to make bubble measurements, ventilation was limited to a narrow 9.6 mm slot at the center of the span. This configuration ensured that bubbles remain mostly within a narrow distance away from the center. Considerable thought was given to obtain a reasonable representative sample of the bubble population that exists when the full span is ventilated. Under this scheme, 45 different experiments were conducted at different water speeds, ventilation gas flow, angles of attack of hydrofoil and the bubbly wake images were obtained at three different axial locations, i.e. 109, 243 and 377 mm from the hydrofoil center. 90,000 bubble images were captured using the SIV technique.

Figure 1: Details of the ventilated foil

Shadow Image Velocimetry technique (SIV) is most suited for analysis of bubbly flows. It employs direct in-line volume illumination using low power sources such as LED and an optical setup to produce a narrow depth-of-field for 2D plane imaging (Goss et al., 2007; Broder and Sommerfeld, 2007). Figure 2 shows a schematic of the experimental setup. A custom-made pulsed LED light source from Innovative Scientific Solutions Inc. was used to illuminate the flow. The pulsed LED array has flash rates up to 10 kHz with a 5 μ s pulse width and rise and fall times $\sim$ 200 ns. To ensure uniform back-lighting in the images, a light shaping diffuser is placed between the light source and the flow, which eliminates noise generated by non-uniform lighting. A 1K $\times$ 1K pixel Photron APX-RS camera (capable of 3000 frames/second at full resolution) with a 60 mm lens was used to obtain images.

In the SIV technique, two LED light pulses separated by a short time are synchronized with camera exposure in order to obtain two consecutive images (or, double frames). The first pulse is

fired at the end of the first exposure and the next at the beginning of the following exposure. In our experiments, the time duration between two pulses was kept 100-230 μs depending on free stream velocity. Using the obtained image pairs, the instantaneous velocity field of the bubbles was obtained using commercially available Particle Image Velocimetry (PIV) software (DaVis 7.2 from LaVision). The image pairs were captured at a frame rate of 25 image-pairs per second and the exposure time for individual images was kept 15 μs to prevent any blurring in the images. A data set consisted of 1000 image-pairs taken over 40 seconds. The field of view of the captured images was approximately 60 mm x 60 mm. The imaging system was calibrated prior to the beginning of the test program using a 2.5 mm x 2.5 mm grid located at the water filled test section centerline. The calibrated images produced by the test program and used in the analysis described here had a constant (square) pixel dimension of 0.059 mm. As mentioned, this pixel dimension was determined by a grid placed at the test section centerline. The bubble plume exited the foil with a spanwise depth equal to the non-masked slot length of 9.6 mm and spread to at most twice this depth at the downstream measurement location. This uncertainty of spanwise bubble location translated to a length scale (and calculated velocity) uncertainty of 1.6% near the foil and 3.2% at the downstream measurement location. The image depth of field was determined to be approximately 15 mm. The bubble sizes were in the range of 2 to 68 pixels, which corresponded to a bubble radius of 0.06 to 2 mm.

Figure 2: Schematic of the experimental setup for shadow imaging of bubbly flows in an aerated hydrofoil wake.

3. Proposed Methods

3.1. Overview of the image-processing task

Figure 3 presents a sample of the original bubble images obtained from our measurements to illustrate a number of challenges involved in the analysis of our images. These challenges include: (1) the spatial and temporal non-uniformities of the image background; (2) a wide range of bubble size distribution; (3) the co-existence of in-focus and out of focus bubbles; and (4) the large bubble clusters.

Figure 3: A sample of original bubbly wake image from our experiments

This spatial non-uniformity, shown as a relatively brighter central disk in Figure 3, is generated by the non-uniform spatial profile of the LED illumination. The temporal non-uniformity in the background is contributed by the fluctuations of LED illumination, and more significantly, by the fluctuating void fraction of bubbles associated with highly unsteady turbulent flows in the field of view. In our experiments, the high ventilation rate and high Reynolds number turbulent flow enhance the bubble break-up and coalescence, which leads to a large dynamic range of bubbles including micro-bubbles to large clusters of several bubbles. In addition, the complexity and three dimensionality of turbulent flows result in a substantial amount of out-of-focus bubbles.

In our case, the conventional methods reported in the literature to deal with these challenges proved to be inadequate. Usually, a background subtraction can be employed to compensate for the temporal non-uniformity. However, since the background illumination intensity varies both

with location and time, the background subtraction can lead to substantial loss of bubble information. Similarly, the spatial non-uniformity caused by the uneven illumination poses a problem for image filtering using either a global, local thresholding or a combination of both. Specifically, for image-filtering using a local thresholding based on block-processing with a suitable filter function, different filter functions have been used in the literature for the determination of threshold value (e.g. Otsu, 1979; Sahoo et al., 1997, Sahoo and Arora, 2004). In the current research, these different filter functions were tried on a variety of images, but were found to be unsatisfactory. It was observed that huge variations in the local void fraction in different images rules out the possibility of a single threshold value for every image or even for small local regions in the image.

These drastic differences in the local void fraction can be attributed to the presence of dense bubble clusters. Usually, bubble clusters are very difficult to deal with and require specific approaches for analysis. Sometimes, these clusters are ignored in the analysis by constraint conditions such as sphericity (Bailey et al., 2005) or concavity index (Mena et al., 2005). From a classical image analysis point of view, it is assumed that bubble clusters occur as a non-selective process and ignoring these clusters would not bias the measurement. However, recently Kracht et al. (2013) showed through a stochastic approach that even if the bubble clusters are non-selective, large bubbles are more likely to be present as clusters. Thus, ignoring these clusters in the measurement would bias the estimations. To consider the size of such bubble clusters, some authors have proposed to approximate the overlapping bubbles through an object recognition approach which fits an ellipsoidal shape to the object areas (Pla, 1996; Honkanen et al., 2005). Some other reports have focused upon segmenting these clusters by implementing watershed algorithm (Bonifazi et al., 1999; Lin et al., 2008; Zhou et al., 2010; Zhang et al., 2011; Lau et al.,

2013). However, a substantial over-segmentation was observed in many cases upon using watershed transform. Such over-segmentation is usually avoided by suppressing the shallow minima using H-minima transform (Gonzalez and Woods, 2004). However, the different variability in the image makes the exact definition of “shallow” minima difficult. In addition, the application of watershed transform requires a pre-processing step to overcome the problems of over-segmentation, which can eliminate small size bubbles in a bubbly flow with a large dynamic range of bubble size. The small size bubbles, because of their large surface area to volume ratio are extremely crucial in our experiments because of their significant contribution to the oxygen transfer as compared to the large size bubbles. Also, there are a large number of small bubbles in the flow field and thus these can’t be ignored.

Finally, it was concluded that to effectively extract the bubble information over a wide size range, to overcome the different non-uniformities in the images and to deal with both in-focus and out-of-focus bubbles, a robust and integrative algorithm is needed.

3.2. Image processing approach

3.2.1. Summary of the Algorithm

Figure 4: Basic outline of the image-processing technique

The proposed approach assumes bubbles are generic ellipsoids and thus the bubble properties such as centroid location, size and shape can be extracted from the projected area of a bubble.

Figure 4 above shows the basic outline of the image analysis procedure. As shown in the figure, the image analysis consists of three major steps: (1) Image binarization: the original grayscale images are converted into binary images using extended H-Minima transform with a suitable parameter (details presented in Section 3.2.2); (2) Bubble categorization: all the bubble regions are labelled and characterized by their position and a series of metrics including area, centroid, major and minor radius and circularity factor. Based on the area of each region, the bubbles are divided into tiny spherical bubbles, intermediate-size bubbles and large bubbles/clusters. (3) Bubble information extraction: Owing to the different sizes and characteristics of bubbles in the images, a single universal approach cannot be used to extract the size information of all the bubbles. Thus, a multilevel segmentation approach is suggested to extract the maximum possible information from the images. A customized approach referred to as ‘Cluster Processing’ (see Section 3.2.3 for details) was developed using advanced morphological operations and a watershed transform to extract individual bubbles from bubble clusters.

3.2.2. Extended H-Minima Transform

H-minima transform of a grayscale image suppresses all minima in the image whose depth is less than a particular value (Soille, 2003). Here, the depth of a minimum refers to the difference in grayscale intensity value of background and the bubble. A unique feature of this technique is that thresholds are applied to the depths of minima and not the grayscale intensity value in itself. Extended H-minima transform is the regional minima of the H-minima transform, where a regional minima is defined as connected components of pixels (8-connected) with a constant intensity value whose external boundary pixels all have a higher value. Thus, the extended H-minima transform of a grayscale image produces a binary image with ‘0’ representing the background and ‘1’ representing the bubble region. It is important to note that the extended H-

Minima transform of an in-focus bubble produces a hole in the bubble region owing to the central bright portion in the bubble. Since extended H-minima transform computes the regional minima and does not require a fixed pre-defined global threshold for the grayscale intensity value for conversion of grayscale image to binary image, it is more robust to the variability in the image caused by fluctuations in background illumination intensity and also because of uneven illumination in the background. Also, the binarization process is not extremely sensitive to the depth-of-minima threshold.

3.2.3. Cluster-processing

Figure 5: A detailed outline of steps in the ‘cluster-processing’ technique for a hybrid cluster

Figure 5 illustrates our approach to extract individual bubble information from bubble clusters. A bubble cluster might contain both in-focus and out-of-focus portions. As shown in Figure 5, the in-focus and out-of-focus portions of a bubble can be distinguished by a central dark hole, which is generated from the central bright portion in the original grayscale images of in-focus bubbles (see Figure 3). However, for the out-of-focus bubbles, only the bubble boundaries can be traced. It is important to note that the narrow ventilation slot in our experiments ensures that bubbles stay near the depth-of-field of our measurements as discussed in Section 2. Based on the

characteristic features of in-focus bubbles, a bubble cluster is divided into the in-focus and the out-of-focus portions and different techniques are employed to segment each portion into individual bubbles. Specifically, first, a set of morphological operations are applied to a bubble cluster (shown in Figure 6) containing both in-focus and out-of-focus portions. These morphological operations resolve only the in-focus bubbles and the out-of-focus bubbles are eliminated in the process. Subsequently, the out-of-focus portion is obtained by subtracting in-focus separated individual bubbles from the original bubble cluster and resolved separately into individual bubbles.

Figure 6 describes the set of morphological operations that were employed to resolve an in-focus cluster into separate bubbles. First, a single cluster is selected with a bounding box around its centroid. Portions of the other contiguous clusters that fall into this bounding box are eliminated based on an area threshold (Figure 6a). The skeletonization of the chosen cluster reduces the foreground regions in the cluster to a skeletal remnant that preserves the shape and connectivity of the original region (Figure 6b). This is followed by a morphological ‘shrink’ operation, which is iteratively performed on the cluster till a point when there is no further change in the skeleton. A shrink operation combined in succession with an area-opening operation removes all the foreground pixels and retains the pixels around the hole. Next, a flood-filling operation was carried out and a complement was taken to obtain a cluster where the boundaries of bubbles are not visible (Figure 6c). The bubble skeleton is then superimposed to obtain the separated bubbles (Figure 6d). Subsequently, a complement and thicken operation was done to offset the effect of iterative shrink operation and finally obtain the separated individual bubbles (Figure 6e, 6f). The structuring element size for the ‘thicken’ operation was chosen in a way so as to ensure that the sum of all separated individual bubble areas equals the total filled area of cluster. Note that, due

to inherent nature of the proposed technique there may be an error of a pixel in resolving the boundary between two different bubbles. Thus, to obtain the actual size of the bubbles, a boundary correction has to be added after the measurements of the bubble size from Figure 6f.

Figure 6: Cluster-processing technique for the in-focus bubble-clusters

The proposed technique essentially depends on the intensity gradients in the bubbles and is limited in resolving the out-of-focus portions of a cluster where intensity gradients are not clearly visible. For this reason, the out-of-focus cluster is resolved into separate bubbles by employing a different technique: watershed segmentation with distance transforms (Chen et al., 2004). The watershed transform is a region-based segmentation technique originally proposed by Meyer (1994), which is based on an analogy with the flooding of a landscape or topographic relief with water (Lin et al., 2008; Zhou et al., 2010; Zhang et al., 2011). This technique requires pre-processing the images by edge detectors and smoothing filters and can otherwise lead to over-

segmentation (Bonifazi et al., 1999). Considering the different sources of variability in the image, it is difficult to use watershed segmentation to resolve all the different sized in-focus bubbles accurately without sacrificing some small size bubble information. Thus, in the current research, we leverage separate approaches for in-focus and out-of-focus bubbles to extract maximum information from our bubble images.

3.2.4. Bubble size and shape measurements

The bubble information including the centroid location, size and shape is extracted based on the projected areas of each bubble in a bubble image. The bubbles are categorized as being circular or elliptical in cross-section and finally bubble size is measured and converted from pixel to metric values using the magnification of the image.

First, all the bubble regions were grouped into three categories based on size: tiny bubbles, intermediate size bubbles and large bubbles/clusters. Based on the observations in our experiments, it is clear that very small bubbles are almost always spherical, i.e have a circular projected area in our images. The area threshold for such tiny bubbles was set to 10 pixels. For these circular bubbles, the radius was computed directly from the area measurements (A) as $d = \sqrt{4A/\pi}$. The intermediate size individual bubbles (10-30 pixels) and the bubbles resolved after ‘cluster-processing’ (> 30 pixels) could have a circular or elliptical projected area. Thus, the bubble shape needs to be determined before the bubble sizes are calculated. The bubble shape is determined by the calculation of Heywood Circularity Factor, defined as $HCF = P/\sqrt{4\pi A}$, where P is the perimeter and A is the area of the region. The Heywood circularity factor is defined as the ratio of bubble perimeter to the perimeter of a circle of the same area. For each bubble, a Heywood circularity factor was calculated. Note that spherical bubbles have a HCF of

unity whereas a square region has a HCF of 1.128. Again, a conservative range of HCF for a circular bubbles was selected to be 0.9 - 1.15. For bubble regions lying within this range of HCF, the radius was determined using the assumption of a spherical bubble. For other bubbles lying outside this range of circularity factor, an ellipse fitting technique proposed by Haralick and Shapiro (1992) was used to determine minor and major axis lengths and the eccentricity of the elliptical projected area.

4. Results and Validation

The proposed image processing technique was validated using both synthetic bubble images and air ventilation rate measured from the experiment.

4.1. Validation through synthetic bubble images

To quantify the precision of bubble size and shape capture, we first implement our approach to synthetic image of a single bubble. Then, polydispersed bubble images that simulate the bubble distribution in our experiments are generated to test the effectiveness of our approach in extracting bubble information from large bubble clusters.

4.1.1. Synthetic bubble generation procedure

The synthetic bubble images are generated using an ensemble of randomly distributed ellipses. The size, eccentricity and orientation of the elliptic objects are also randomly selected within the range of bubble characteristics measured from the experiments. As illustrated in Figure 7, an intensity profile, approximated using the quadratic function below, is superimposed on each ellipse to reproduce the intensity profile of bubbles from the experiments. The intensity at any radial position, r is defined by the quadratic:

$$I = ar^2 + b$$

where,

$$a = \frac{(I_m - I_i)}{R^2} ; b = I_i \quad \text{if } |r| < R$$

$$a = \frac{(I_b - I_m)}{(R_2^2 - R^2)} ; b = I_m - \frac{(I_b - I_m)R^2}{(R_2^2 - R^2)} \quad \text{if } R_2 > |r| > R$$

I_m , I_i and I_b correspond to different fixed pixel intensity values in a bubble image as shown in Figure 7. I_m refers to the minimum intensity in the bubble cross-section, I_i is the intensity of the central bright portion of the bubble and I_b refers to the background intensity of the bubble images. The bubble radius is given by: $R_2 = R + w$, where w is bubble width. The bubble centroid is chosen as the origin of the co-ordinate system. Thus, a generic elliptical synthetic bubble image was synthesized with the prescribed intensity profile that matches that of an actual bubble.

4.1.2. Single Bubble Measurement

To validate the proposed image analysis algorithm, we employ a methodology similar to that reported by Lau et al. (2013). First, we apply the image processing algorithm on single synthetic bubbles for different sizes and shapes (i.e. circular and elliptical). An elliptical shaped bubble is drawn with a specific radius in pixels and its centroid is placed in the middle of a pixel (0.5 pixel, 0.5 pixel). Subsequently, 50 new bubbles with same size and shape are generated with its centroid translated with steps of 0.01 pixel in both x and y direction. For each translation, the image analysis algorithm calculates the bubble equivalent radius and the percentage error in measurement of bubble area-equivalent radius is calculated. The bubble area-equivalent radius is

the geometric mean of the minor and major radius of a bubble. The average size and range is presented as error bar in Figure 8. The same process is repeated for bubbles of different radius ranging from 5 to 105 pixels and for both elliptical (eccentricity = 0.6) and circular bubble shapes. Figure 8 presents a comparison of the error in radius measurement for the circular bubbles, elliptical bubbles and the maximum possible uncertainty in the measurement estimated by Lau et al. (2013).

Figure 7 : (a) An actual bubble image and (b) its corresponding intensity profile is used to replicate (c) a synthetic bubble image and (d) its intensity profile. (e) A synthetic bubble image showing different parameters involved in bubble generation.

Figure 8: Error in radius measurement of a single bubble for both circular and elliptical bubbles (eccentricity = 0.6). Green line shows an estimate of the error which was mathematically obtained by Lau et al., (2013). The dots show the mean error whereas the error bars show the maximum and minimum errors.

For both circular and elliptical bubbles, it was observed that as the area-equivalent radius increased, both the absolute error in the measurement of the bubble size and the uncertainty decreased. The mean error in the size measurement of a single circular bubble decreased from 4.22 % at a radius of 5 pixels to about 0.21% at a radius of 104 pixels. The errors in the measurement of an elliptical bubble were found to be slightly greater than the circle with same area-equivalent radius. The mean error in the measurement of an elliptical bubble varied from 5.77% at an area-equivalent radius of 6 pixels to 0.84% at an area-equivalent radius of 104 pixels. For the same area-equivalent radius, the larger uncertainty associated with the elliptical bubble compared to a circular bubble can be attributed to the greater uncertainty involved in the measurement of the minor radius of elliptical bubble, which is smaller than the area-equivalent

radius. The uncertainty in the measurement of the bubble size can be caused by many factors such as inhomogeneous background illumination, and background fluctuations due to out-of-focus bubbles etc.

4.1.3. Polydisperse bubble size distribution measurement

To further validate the effectiveness of the image-processing approach to extract the individual bubbles from bubble clusters, we applied our analysis technique to synthetic bubble images resembling the bubble distributions from our experiments, with average number of bubbles exceeding 500 and void fraction ranging from 0.1 to 0.7. Figure 9a shows a sample of a synthetic bubble image with 900 bubbles. The bubbles were randomly placed in a 1024 x 1024 pixel grid and the bubble eccentricity was randomly chosen between 0 and 0.9, which is the range of eccentricity of bubbles observed in our experiments. The results after the image processing are illustrated in Figure 9b. The red and cyan ellipses denote the in-focus and out-of-focus large bubbles/clusters respectively (the bubbles segmented by the cluster-processing step), the yellow ellipses correspond to the intermediate size bubbles and the magenta dots correspond to tiny spherical bubbles. As the figure shows, all the bubbles are well segmented and the clusters are mostly very well resolved.

Figure 9: (a) A synthetic bubble image and (b) the corresponding output from the described image-processing algorithm.

A more quantitative assertion of the efficacy of the current approach is provided by a comparison between the probability density function (PDF) of the actual input bubble size distribution and the PDF obtained after applying the image analysis algorithm to the synthetic bubble image as shown in Figure 10.

Figure 10: PDFs of bubble size distribution

The input bubble size distribution was a bimodal distribution with peaks at 0.1 and 0.4 mm, which correspond to a radius of 2 pixels and 8 pixels, respectively. In general, the output PDF from our image analysis showed a good match with the input fraction of bubbles at different sizes, although a slight deviation can be observed for the intermediate bubbles in the bubble radius range of 0.15 – 0.45 mm. In addition, the image-processing algorithm captures the bimodal distribution quite well and the magnitudes in the PDFs are in good agreement.

A more comprehensive assessment of our approach is provided by implementing it on bubble images generated with different void fractions in the range of 0.02– 0.66 and comparing the Sauter mean diameters (d_{32} or SMD) obtained from our analysis with the input. According to Ferriera et al. (2012), the SMD is a significant scale for characterizing mass transfer during the interfacial processes, which is defined as

$$SMD = \frac{\sum_{i=1}^N n_i d_i^3}{\sum_{i=1}^N n_i d_i^2}$$

Where, $d_i = \sqrt{a_i b_i}$, a_i and b_i are major and minor axis lengths of the bubble projected area, n_i is the number of bubbles with a particular diameter d_i and N is the total number of bubbles in an image. In general, an increase of SMD corresponds to a decrease of surface-to-volume ratio and implies an increasing portion of larger size bubbles in the image. Hence, as the number of large bubbles in the image increased leading to a change in void fraction from 0.02 to 0.66, the actual SMD increased from 0.21 to 0.71 mm. Bubble images were synthesized with different void fraction values. As the void fraction increased, there was greater overlap between bubbles. For each of these synthesized images, the actual SMD is calculated as the SMD of all the bubbles in the image. Then, the image-processing algorithm was applied and the SMD of all the detected bubbles is calculated. Then, this measured SMD is plotted against the actual SMD for all the images and is shown in Figure 11. As it shows, the measured SMD is in good agreement with the input results with errors staying within 6-8%. This uncertainty in the measurement can be attributed to the limitation of the image-processing algorithm to accurately resolve highly overlapping bubbles, particularly when individual bubbles completely overlap with clusters, and also to the errors due to non-uniformity in the image background.

Figure 11: Comparison of actual and measured SMD obtained from synthetic bubble images (The blue line has a slope of 1)

4.2. Experimental validation of the image-processing approach

The bubble information extracted from our image analysis can be used to estimate the ventilation flow rate during the experiments, which can be compared with the ventilation rate measured from the mass flow controller to validate the efficacy of our image analysis technique. Note that for this comparison, air absorption in the bubbly wake is neglected considering the small time-scales ($< 1s$) between air injection and image capture. For such a small time-scale, gas transfer measurements in the bubbly wake indicate a maximum possible increase in dissolved oxygen concentration to be 10^{-5} ppm. Thus, the mass flow rate of air at the two locations can be considered almost equal.

The estimation of ventilation rate from bubble images consists of three steps: (1) extract 2D bubble size information, (2) obtain the volume and velocity of individual bubbles, and (3)

calculate the volume flow rate from the volume and velocity information of all the bubbles accounting for the changes in pressure and temperature.

In the first step, the extraction of 2D bubble information is accomplished by the proposed image-processing technique. In this step, the semi-major axis (a) and semi-minor axis (b) lengths of the elliptical bubbles are determined. Second, an elliptical bubble is rotated around its major axis to obtain a prolate spheroid or an ellipsoid of revolution. Then, the volume of this prolate spheroid can be mathematically determined as $(4\pi/3)b^2a$. Figure 12 presents the mean streamwise velocity of bubbles in the wake obtained using SIV technique as described in Section 2. As it is shown in Figure 12, the bubble velocity remains almost uniform in the wake, varying within 5% of about 5 m/s. It is noteworthy that a non-symmetric velocity field is observed with higher velocity above the centerline since the ventilated air is injected from the pressure side of the hydrofoil located below the centerline.

Figure 12: The mean horizontal velocity field obtained using SIV technique (The origin in this contour plot is located at a distance of 377 mm from hydrofoil center of rotation). The units on the colorbar are m/s.

Finally, in the third step, the volume and velocity information of all the bubbles are used to calculate the volume flow rate. To compare with the corresponding volumetric flow rate at standardized temperature and pressure as obtained from the mass flow controller, the volume flow rate measured from bubble images is adjusted with respect to the pressure and temperature in the test-section. It is expected that if the ventilation flow rate is measured at any downstream location in the wake based on the bubble images, the measured ventilation flow rate should match the ventilation rate actually introduced in the flow. In our experiments, the images were captured at three different downstream locations and the ventilation flow rate was measured at all three locations. Finally, steps 1 and 2 are repeated for all the bubbles to obtain a predicted flow rate for one single image. This expression is given by

$$\dot{Q}_{total} = \frac{\beta^3}{M} \sum_{k=1}^M \dot{Q}_{single,k}; \quad \dot{Q}_{single} = \sum_{i=1}^N \left(\frac{u_i}{w} \right) \left(v_i \times \frac{P_{TS}}{P_0} \times \frac{T_0}{T_{TS}} \right); \quad v_i = (4\pi/3) a_i b_i^2.$$

Where M and N denote number of images over which averaging is done (M = 1000 for our experiments) and the total number of bubbles in a single image, respectively. β represents spatial resolution and w refers to the width of a single bubble image (1024 pixels or 60 mm). u_i and v_i signify velocity and volume of individual bubbles, respectively. Finally, P_0 and T_0 correspond to ambient temperature and pressure, and P_{TS} and T_{TS} are corresponding test-section conditions. The volume flow rate is averaged over all the 1000 images to obtain the mean ventilation rate. Figure 13 below shows the measured mean ventilation rate values at each of the three different downstream locations:

Figure 13: The measured volumetric flow rates as a function of downstream distance in the bubbly wake compared with the input flow rate of 0.5 SLPM (shown in blue)

As the figure above shows, the measured mean ventilation volumetric flow rates compare well with the actual volumetric flow rate of 0.5 SLPM., with the difference within 9% of the actual

value at all the three downstream locations. As the clustering phenomena reduces downstream away from the hydrofoil, the mismatch decreases to less than 1%. Larger mismatch occurring closer to the hydrofoil is likely to be associated with the higher uncertainty in extracting bubble information from very dense bubble clusters. The clustering of the bubbles underestimates the volumetric flow rate. This indicates that the accuracy of the image processing technique decreases with excessive clustering.

5. Conclusions

In this paper, a robust image measurement technique is proposed to measure the bubble size distribution in dense bubbly flows. The proposed image analysis technique divides all the bubbles into different categories including bubbles within different size range and bubble clusters based on bubble morphology and size. The bubble clusters are passed through an additional step that resolves clusters into individual bubbles. Based on the intensity gradient at the center of individual bubbles, a bubble cluster is divided into in-focus and out-of-focus portions, which are subsequently segmented using ‘cluster-processing’ and watershed segmentation with distance transform, respectively. We implement the proposed technique to obtain bubble information within a wide size range of $120\ \mu\text{m} - 4\ \text{mm}$ from the images acquired in ventilation experiments for highly turbulent bubbly flows. The image analysis technique was first validated using synthetic bubble images. A further validation was performed by comparing volumetric airflow rates derived according to the bubble size information obtained using the proposed technique with those measured from a mass flow controller.

As the result shows, the image analysis approach is able to capture the size, shape and location information of both in-focus and out-of-focus bubbles from bubble shadow images acquired using SIV technique. In our experiments, the bubble eccentricities largely varied from 0 to 0.9

and the technique was found to be robust enough to accurately resolve the overlapping bubble clusters in this range of bubble eccentricity. Further, the image analysis approach was also applied to simulated bubble images which had some overlapping elliptical bubbles with high eccentricity ($0.95 < e < 1$) and the results proved the efficacy of the image analysis approach in resolving such clusters. Although the proposed approach was found to work well at a wide range of void fractions (0.02 – 0.7), it was found that as the bubble clustering reduced, the accuracy of the technique to resolve the bubble clusters increased. Last but not the least, the proposed image analysis technique is computationally efficient. For instance, using an Intel® Core™ i5-3320M (2.60 GHz, 4 GB Memory) processor, the average processing time per image ranged from 3 – 10 seconds. Therefore, with further development on the parallelization of the algorithm over multiple cores, the proposed technique will allow real-time monitoring of bubble distribution for a wide range of industrial applications. The proposed technique can be broadly applied to bubble characterization in different experimental facilities (e.g. inclined, vertical channels, etc.), as well as other types of two-phase flows such as sprays, drops and froth to quantify void fraction, gas hold-up and size distribution of the dispersed phases.

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