

Development of Advanced Image Processing Algorithms for Bubbly Flow Measurement

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ABSTRACT

An accurate measurement of bubbly flow has a significant value for understanding the bubble behavior, heat and energy transfer pattern in different engineering systems. It also helps to advance the theoretical model development in two-phase flow study. Due to the interaction between the gas and liquid phase, the flow patterns are complicated in recorded image data. The segmentation and reconstruction of overlapping bubbles in these images is a challenging task. This dissertation provides a complete set of image processing algorithms for bubbly flow measurement. The developed algorithm can deal with bubble overlapping issues and reconstruct bubble outline in 2D high speed images under a wide void fraction range. Key bubbly flow parameters such as void fraction, interfacial area concentration, bubble number density and velocity can be computed automatically after bubble segmentation. The time-averaged bubbly flow distributions are generated based on the extracted parameters for flow characteristic study. A 3D imaging system is developed for 3D bubble reconstruction. The proposed 3D reconstruction algorithm can restore the bubble shape in a time sequence for accurate flow visualization with minimum assumptions. The 3D reconstruction algorithm shows an error of less than 2% in volume measurement compared to the syringe reading. Finally, a new image synthesis framework called Bubble Generative Adversarial Networks (BubGAN) is proposed by combining the conventional image processing algorithm and deep learning technique. This framework aims to provide a generic benchmark tool for assessing the performance of the existed image processing algorithms with significant quality improvement in synthetic bubbly flow image generation.

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GENERAL AUDIENCE ABSTRACT

Bubbly flow phenomenon exists in a wide variety of systems, for example, nuclear reactor, heat exchanger, chemical bubble column and biological system. The accurate measurement of the bubble distribution can be helpful to understand the behaviors of these systems. Due to the complexity of the bubbly flow images, it is not practical to manually process and label these data for analysis. This dissertation developed a complete suite of image processing algorithms to process bubbly flow images. The proposed algorithms have the capability of segmenting 2D dense bubble images and reconstructing 3D bubble shape in coordinate with multiple camera systems. The bubbly flow patterns and characteristics are analyzed in this dissertation. Finally, a generic image processing benchmark tool called Bubble Generative Adversarial Networks (BubGAN) is proposed by combining the conventional image processing and deep learning techniques together. The BubGAN framework aims to bridge the gap between real bubbly images and synthetic images used for algorithm benchmark and algorithm.

Dedication

This dissertation is dedicated to my family.

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I would like to thank my advisor, Professor Yang Liu for his guidance over the past five years. It has been a great pleasure to work with such a diligent and brilliant person that I have ever meet. In his research group, ideas are always encouraged and I was given good freedom to explore the challenges in the field of two-phase flow study. This dissertation would not have been possible without his insight and instruction.

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1 Introduction

1.1 Research Background

Bubbly flow measurement is one important but challenging task in studying two-phase flows. Bubbles and surrounding liquid flow can form a four-way coupling system, which involves complex hydrodynamic forces between two phases and various bubble interaction mechanisms. Commonly used engineering models employ a certain averaging algorithm to simplify the mathematical description of the complex bubbly flow phenomena [1]. Measurement of averaged quantities including bubble number density, void fraction, interfacial area concentration distributions are of practical interest to provide a database for the development and benchmarking of various two-phase flow models. In multiphase computational fluid dynamics (CFD), the initial distribution and boundary conditions from measurement are also necessary to meet the modern validation experiment requirements [2].

Techniques used for bubbly flow measurement can be largely classified into two groups, namely, intrusive and non-intrusive methods. Typical intrusive methods applied in bubbly flow measurement include fiber optic probe [3], conductivity probe [4–7], sampling probe [8], phase-sensitive constant temperature anemometry [9] and wire-mesh sensors [10]. Non-intrusive methods include x-ray [11,12] or γ -ray computed tomography [13,14], laser Doppler anemometry [15] and image processing technique [16–19]. The intrusive methods require direct contact of the instrument with the flow during the measurement. This may cause undesired disturbance in the flow field. The spatial resolution of intrusive methods is usually not very high since a probe or a wire-mesh sensor can measure one or a limited number of discrete points at a time. Increased number of measurement points will increase flow disturbance and consequently the uncertainty of the data. Non-intrusive methods do not require direct contact with the flow field, which keeps the disturbance to a minimum. With the major development of digital imaging technique in recent years, image processing combined with high speed camera imaging system has become a promising technique for bubbly flow measurement due to its capability in obtaining high spatial and temporal resolution data.

Depending on the available camera number and the complexity of the measured flow condition, the image processing technique used for bubbly flow measurement can be different. In the early 1970's, single high speed camera has been used to measure single bubble terminal

velocity and to develop the drag force correlation [20–22]. In these studies, the measured objects usually are single bubbles with no overlapping issues. The used image processing techniques are relatively simple. The bubble outline can be acquired by binarizing high speed images. In a later stage, the image processing techniques were extended to process bubbly flow images. A wide variety of information such as bubble size, number density, and velocity can be acquired from bubbly flow images [16,23–26]. Recently, extensive studies have been carried out on automatically extracting and analyzing more complex bubbly flow image with a higher void fraction [27–30]. In these studies, bubble parameters are mostly extracted from the silhouette of the bubble projection in the image. With certain assumptions such as the bubble is axisymmetric along the velocity direction, the bubble volume and surface area can be estimated from the projection outline as well. For low Morton number system like an air-water system, the bubble volume should be averaged over a sequence of frames to reduce the error caused by bubble rotation or shape oscillation during the measurement. The time- and spatial-averaged two-phase parameters can be calculated accordingly once the information of individual bubbles is extracted from the image. These image processing algorithms to process 2D high speed images recorded from single high speed camera can be classified as 2D image processing techniques.

The time- and spatial-averaged data can be used to study the behavior of two-phase flow systems. However, they may not contain sufficient details for studying individual bubbles. For example, the bubble aspect ratio is reported to be an important factor which may influence bubble terminal velocity [31,32]. While being important for bubble dynamics, the bubble shape deformation, rotation and aspect ratio can not be recovered directly with 2D image processing algorithm and the single camera system. A single camera can only detect the bubble rotation along the camera axis. For the rotation along the axes parallel to the image plane, the single camera system cannot obtain this information directly. In this case, the bubble aspect ratio estimated from the single camera may have large uncertainty [33]. To overcome the above challenges, several recent experimental works [16,34–36] have used two orthogonal high speed cameras for single bubble measurement. With two high speed cameras, the bubble volume and surface area measurements are expected to be improved over a single camera system as more information is available. Another dimension is also added to the bubble rotation angle and aspect ratio measurement. For these multiple camera systems, the 3D bubble shape will be reconstructed by

combining the bubble projection outlines from different cameras together. With a more accurate bubble shape, it is expected that the bubbly flow measurement accuracy can be further improved.

For 2D image processing algorithms, the technical challenges are summarized in Fig. 1.1. Take images with backlit illumination setup as an example, an ideal spherical bubble usually results in a circular shape with a dark edge and bright center in the image. In experiment images, the bubble shapes are much more complicated. The disturbances introduced by bubbles and liquid turbulence may affect the shape and motion of nearby bubbles. Large bubble surface tends to be more unstable due to increased inertia effect. If a bubble is disturbed by the surrounding flow, or becoming unstable, or going through a coalescence or breakup process, its surface can be distorted and take an arbitrary shape. When projected to the image plane, these bubbles may be elongated or appear darker with edges become thicker than normal spherical or ellipsoidal bubbles. At high void fraction, bubble overlapping becomes another challenging issue in image processing. In a cluster of overlapping bubbles, part of the bubble information is missing in the image. It may be difficult to accurately identify each bubble and reconstruct their actual boundaries. If not handled properly, the result such as bubble number density, void fraction will contain significant errors. For a large cluster of bubbles, how to correctly group the separated arcs that belong to the same bubble is another problem. Some bubbles in the middle of the cluster may have three or four separated arcs. If these arcs are not classified correctly, the bubble number and the final reconstructed bubble shape will be incorrect.

In terms of 3D bubble reconstruction, existed 3D imaging system usually use two synchronized orthogonal high speed cameras for this task. For high Morton number system where a bubble has relatively small deformation, two camera system may have very good accuracy. However, it should be pointed out that typical bubbles found in different industrial systems have very complicated shape and they deform constantly in two-phase flows. These bubbles cannot be described by simple functions such as those used for spheres or ellipsoids. In this case, the bubble shape measurement can be difficult even with two camera systems.

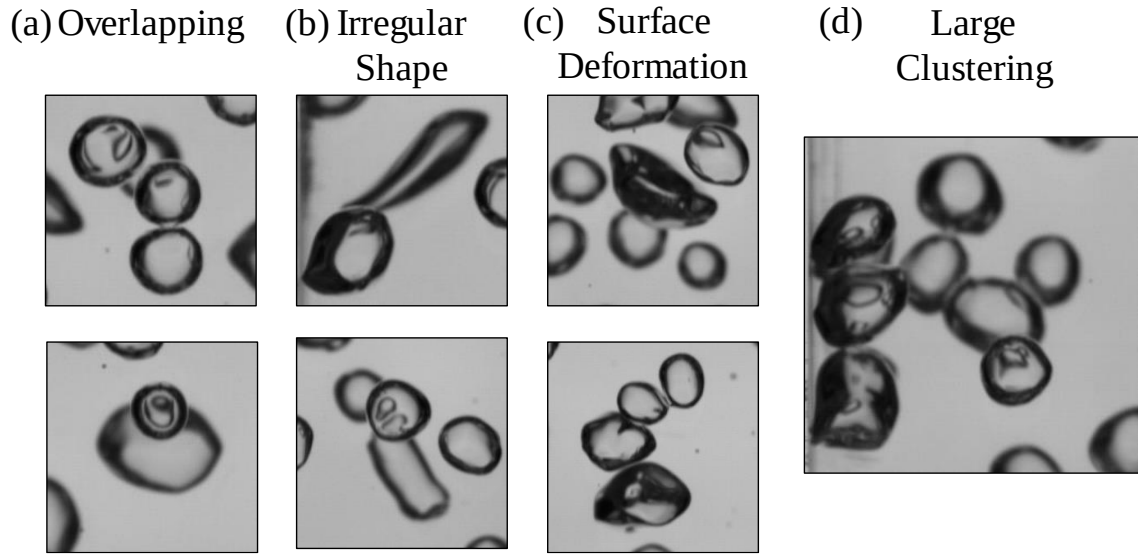


Fig. 1.1 Sample bubbly flow images showing various technical difficulties in image processing (a) bubble overlapping along camera axis, (b) irregular shape bubble formed by liquid turbulence and/or during bubble coalescence and breakup, (c) large bubble appeared in a dark solid shape due to surface deformation , (d) large cluster of bubbles in high void fraction condition.

1.2 Dissertation Objective

The presented researches in this dissertation aim to develop a set of advanced image processing algorithms to address the aforementioned issues in bubbly flow measurement. The presented algorithms in this work consist of three major parts: 2D image processing algorithm, 3D bubble reconstruction algorithm and algorithm benchmarking tool (BubGAN).

The main objectives are listed as follows:

Part 1: 2D Image Processing Algorithm

- Develop a new 2D image processing algorithm capable of handling bubble overlapping at high void fraction condition;
- Evaluate the 2D image processing algorithm with synthetic and experimental data;
- Study the characteristics of bubbly flow using the proposed algorithm.

Part 2: 3D Bubble Reconstruction Algorithm

- a) Develop a new 3D bubble reconstruction algorithm which is applicable to multiple camera systems;
- b) Evaluate the reconstruction algorithm with synthetic data and syringe test;
- c) Evaluate the one-, two- and multiple-camera imaging system for bubbly flow measurement;
- d) Study the wall influence on bubble rotation and aspect ratio change.

Part 3: Bubble Generative Adversarial Networks (BubGAN)

- a) Develop an algorithm for synthetic bubbly flow image generation with more realistic bubbles compared to traditional mathematical model;
- b) Develop a million-bubble database and related bubbly flow image generation tools for algorithm benchmarking and automatic deep learning algorithm labeling;

1.3 Dissertation Outline

In Chapter 2, a 2D image processing algorithm is proposed to automatically separate and reconstruct the overlapped bubble in recorded high speed images. The proposed algorithm combines the bubble geometrical, optical and topological information for segmentation to yield robust and high accuracy results. The common difficulties such as overlapping, irregular bubble shape, surface deformation and large clustering in bubbly flow images are addressed by providing a preset decision table and flow chart using the aforementioned bubble information. The performance of the algorithm is evaluated by synthetic bubbly flow images with the area-averaged void fraction ranging from 2.4% to 18%.

Followed by Chapter 2, the proposed image processing algorithms are used to process eight bubbly flow runs with various liquid and gas flow rates in Chapter 3. The data is recorded in a rectangular channel with the cross section size of 30 mm x 10 mm. The test facility runs air-water upward flows at room temperature and near atmospheric pressure conditions. Three high speed cameras are synchronized to recorded the bubbly flow images facing the 30 mm width side at a rate of 1000 frames per second (fps). The transverse distribution and axial development of various parameters are analyzed with the processed data. The void fraction measurement is compared with the double-sensor conductivity probe in the transverse direction. At the end of this chapter, the

acquired bubbly flow data are used for interfacial area transport equation (IATE) and bubbly number density transport equation benchmark.

In Chapter 4, a 3D imaging system is built with four synchronized high speed cameras. This system can capture each individual bubble in four different views. Combining with the space carving algorithm, the system can reconstruct the 3D bubble shape with minimum assumptions. A test was carried out by injecting 331 bubbles in the test section. The 1-camera, 2-camera and the current 4-camera system are compared for void fraction measurement accuracy. The wall influence on the bubble rotation and aspect ratio is then explored with the known bubble 3D shape, which is not practical with only 1 or 2 cameras.

In Chapter 5, the BubGAN framework is proposed to generate realistic synthetic bubbly flow images. The BubGAN combines the 2D image processing algorithms and the generative adversarial networks (GAN). The BubGAN inherits the advantages of GAN, which can generate realistic images given related training data. It can also directly provide the labeling information of each bubble in the generated bubbly flow images, which is not possible with traditional GAN. The proposed BubGAN has full control of bubble aspect ratio, orientation, circularity. With this framework, the accuracy for algorithm benchmark is expected to have a significant improvement. Finally, a summary of the dissertation is provided in Chapter 6.

The contents in Chapter 2 to Chapter 4 are based on the published works done by the author in his Ph.D. period [37–39]:

Y. Fu, Y. Liu, Development of a robust image processing technique for bubbly flow measurement in a narrow rectangular channel, *Int. J. Multiph. Flow.* 84 (2016) 217–228.

Y. Fu, Y. Liu, Experimental study of bubbly flow using image processing techniques, *Nucl. Eng. Des.* 310 (2016) 570–579.

Y. Fu, Y. Liu, 3D bubble reconstruction using multiple cameras and space carving method, *Meas. Sci. Technol.* 29 (2018) 075206.

2 2D Image Processing Algorithm for Dense Bubbly Flow Measurement

2.1 Introduction

To automatically processing the recorded bubbly flow images, many 2D image processing algorithms have been proposed to deal with the common overlapping issues in the past. The related works can be summarized in Table 2.1. In general, there are two major steps to process bubbly flow images. The first step is bubble segmentation, namely, to separate overlapping bubbles in a cluster and identify the right number of bubbles. The second step is to reconstruct the missing part of each individual bubble and correct any artifacts if necessary.

For bubble segmentation, Hough transform [40], breakpoint method [41,42] and watershed method [43,44] are the most used techniques. The Hough transform is good for detecting circular shape objects as shown by Hosokawa *et al.* [31] in micro bubble measurement, by Prakash *et al.* [45] in bubbles affected by turbulence, and by Yu *et al.* [46] and Mathai *et al.* [47] in solid particle measurement. It has good accuracy for small spherical bubbles or solid spheres. The result becomes less accurate for large size bubbles with irregular shapes. For non-spherical bubble cluster, Honkanen *et al.* [16] and Honkanen [48] used the breakpoint method to separate overlapped bubble boundaries in the cluster. The unoccluded edges for each bubble can be obtained by this method. The watershed method is used by Lau *et al.* [27] and Karn *et al.* [29] to separate the clustered bubble groups consisting of various sizes. Optical properties such as the intensity difference between bubbles and background are used by Bröder and Sommerfeld [33] to detect bubble outline for nonclustered bubbles. Ferreira *et al.* [49] proposed to use the shape complexity to classify solitude and clustered bubbles.

For bubble reconstruction, the most used method is to connect the missing section on bubble boundary with a straight line or to fit an ellipse based on the extracted outline arcs for the bubble. Considering the complexity of the bubbly flow, using one method for cluster separation and bubble reconstruction will have very limited applicability. For the watershed method, the over- and under-segmentation are common problems found in the past studies. One single bubble can be divided into several separated objects if the shape is elongated. If two bubbles are too close to each other, they can be grouped as one object in the image. To detect bubble boundary based on intensity gradient may result in different recognition rate for in-focus and out-of-focus bubbles with a certain threshold. For the breakpoint method, using one threshold is not always robust to correctly identify

all breakpoints. Deformed bubbles can cause over-segmentation. The breakpoint may not be detected if two bubbles are too close and are smoothly overlapping in the image. With these difficulties, most existing studies attempting to extract all the bubbles in the image are limited to void fraction less than 7%. Note that Ferreira *et al.* [49] applied their algorithm to void fraction up to 11%. However, their algorithm did not separate the overlapping bubbles. The uncertainty in bubble number density and void fraction data may need further assessment. For bubbly flow with void fraction higher than 15%, it is usually not possible to extract all the bubbles in the image. By reducing the depth of field or using the telecentric lens [50], the front bubbles can be extracted in these cases.

To overcome the issues discussed above and extend the method to higher void fraction conditions, a robust image processing technique is proposed to separate and reconstruct the overlapping bubbles in the images. The proposed algorithm utilizes the image intensity, geometry and topology information in order to separate the overlapping bubbles in a cluster. Decision table and flowchart are provided when combining the information from different aspects to find the most accurate result in processing these clustered bubbles. After obtaining the separated bubble segments, a reconstruction procedure is performed to complete the missing sections. Both the inner edge and outline of typical bubble images are used during reconstruction. This preserves the most information of the original image and avoids the uncertainty introduced from simple ellipse fitting.

It should be noted that this method deals with the segmentation and reconstruction of bubble projections in 2D images. The goal of this method is to obtain accurately the number of bubbles and the outline of each individual bubbles. The 3D bubble reconstruction, or bubble volume and surface area information are not directly available with 2D images. However, the information obtained by the present algorithm will be essential for the determination of these 3D quantities. Such discussions will be presented in Chapter 4 with multiple camera system.

In the following, the experiment setup consisting of a rectangular channel for two-phase flow visualization will be described first. Then the details of the 2D image processing algorithm will be discussed. The algorithm is then benchmarked by generating synthetic bubble images.

Table 2.1 Summary of image processing schemes for bubbly flow available in the literature.

Reference	Test Section	Void Fraction	Bubble Size	Bubble Segmentation	Bubble Reconstruction
(Honkanen, 2009; Honkanen <i>et al.</i> , 2005)	Round Pipe $D=105$ mm	$\leq 2\%$	0.01-2 mm	Breakpoint	Ellipse fitting
(Zaruba <i>et al.</i> , 2005)	Rectangular Channel 100 mm $\times$ 20 mm	$\leq 4\%$	1-4 mm	N/A	N/A
(Bröder and Sommerfeld, 2007)	Rectangular Channel 300 mm $\times$ 100 mm	0.5% - 5%	2-4 mm	Edge intensity gradient	Use bubble with 85% contour detected
(Hosokawa <i>et al.</i> , 2009)	Round Pipe	N/A	0.08-1 mm	Hough transform	N/A
(Yu <i>et al.</i> , 2009)	Round Pipe $D=9$ mm	N/A	2.38 mm	Hough transform	Ellipse fitting
(Lelouvetel <i>et al.</i> , 2011)	Round Pipe $D=44$ mm	0.5-1%	1.18-2.87 mm	N/A	N/A
(Ferreira <i>et al.</i> , 2012)	Rectangular Channel 140 mm $\times$ 20 mm	$\leq 11\%$	4.5-7.5 mm	Shape complexity*	N/A
(Prakash <i>et al.</i> , 2012)	Rectangular Channel 0.45 m $\times$ 0.45 m	N/A	2.5-3.15 mm	Hough transform	N/A
(Lau <i>et al.</i> , 2013)	Rectangular Channel 200 mm $\times$ 30 mm	6.8 %	2-6 mm	Watershed	Ellipse fitting
(Karn <i>et al.</i> , 2015)	Rectangular Channel 1 m $\times$ 0.19 m	N/A	0.1-1 mm	Watershed; Morphological characters	N/A

*The shape complexity method is used to classify different types of bubble clusters. No actual segmentation is carried out in this method.

2.2 Experimental Setup

The schematic of the test facility used for two-phase flow study is shown in Fig. 2.1. The facility is designed to run adiabatic air-water upward flow at room temperature and atmospheric pressure. The test section is 3 m tall and has a 30 mm $\times$ 10 mm rectangular cross section. The hydraulic diameter of this test section is $D_h = 15$ mm. A variable speed water pump is used to deliver the desired flow rate to the test section from a storage tank. Air flow is supplied by the building compressed air line and regulated by a pressure regulator. Two-phase mixture leaving the test section are separated by gravity in the storage tank. The water circulates through the loop and air is vented to atmosphere. Air and water are mixed at a two-phase injector, as shown in Fig. 2.1 (b) which consists of two opposite facing aluminum plates installed flush with the 30 mm wide walls. On each plate, there are five 200 μm holes from where the air is injected into the flow channel. This design can result in a symmetric bubble distribution at the test section inlet. Two magnetic flow meters are used to measure the water flow rate entering the test section with an accuracy of $\pm 1\%$ of the actual reading. The air flow is measured by four gas flow meters based on the laminar differential pressure flow technology, which also has an accuracy of $\pm 1\%$ of the actual reading. By controlling air and water flow rates, various bubbly flows with different void fractions can be obtained in the test section.

From bottom to top, three transparent imaging windows are available for flow visualization. It can also serve as the instrumentation port for probe measurement if required. They are located at the dimensionless height of $z/D_h = 8.8, 72.4$ and 136 . An enlarged view of port 3 in Fig. 2.2 shows a typical setup of the imaging system with a single high speed camera. The high speed cameras are set to face the 30 mm wide side of the test section. On the opposite side, a LED panel is installed to provide backlight illumination to the test section. The acquired image usually can have a resolution of around 25 pixels per mm, varying accordingly to the camera distance to the test channel. High speed images are usually recorded at the frame rate of 1000 frame per second (fps).

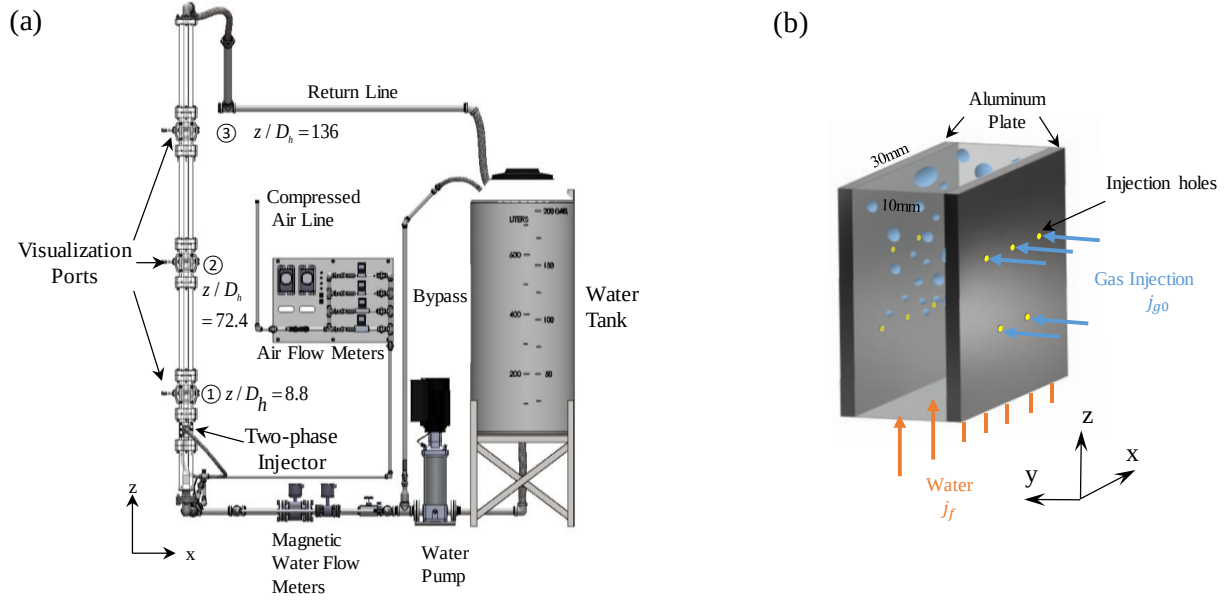


Fig. 2.1 (a) Schematic of the experimental facility capable of running adiabatic air-water two-phase flows in vertical upward direction. (b) Schematic of the two-phase flow injector at the bottom of the test loop.

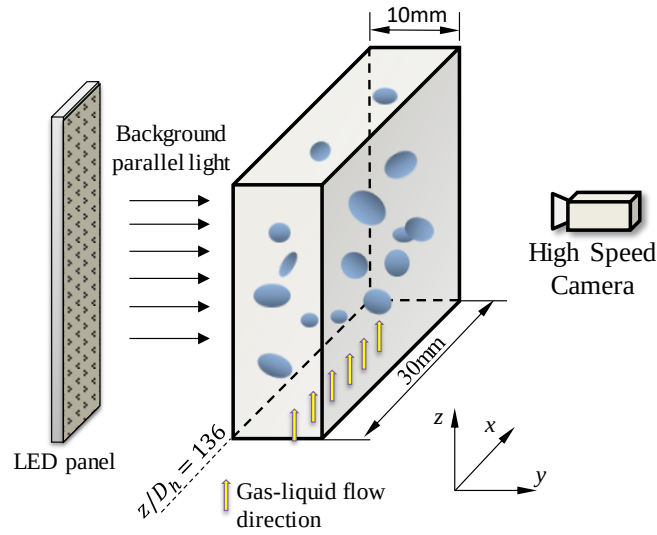


Fig. 2.2 Schematic of image system setup at the third visualization port $z/D_h = 136$.

Different two-phase flow patterns are visualized in Fig. 2.3. These images are recorded at the three visualization ports with three high speed cameras (Photron FASTCAM SA4 at $z/D_h = 8.8$ and 72.4, Photron FASTCAM SA6 at $z/D_h = 136$). Five typical flow regimes, namely, bubbly, cap-bubbly, slug, churn-turbulent and annular flow are recorded. The development of the flow pattern from bottom port 1 to the top port 3 can be identified by referring to the three images recorded for each flow regime.

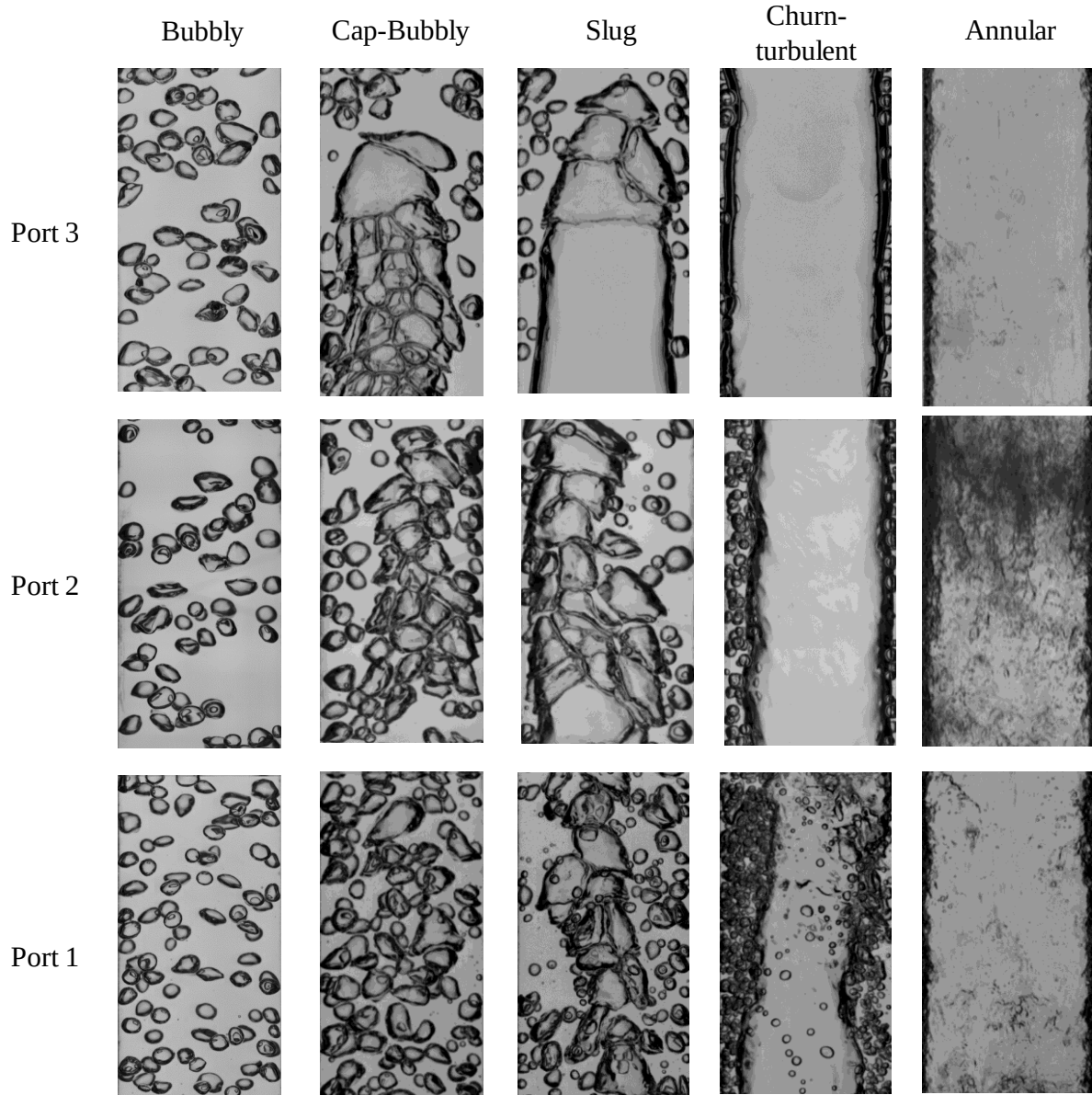


Fig. 2.3 Typical air-water two-phase flow images recorded at the three visualization ports. From left to right, the bubbly, cap-bubbly, slug, churn-turbulent and annular flow regime are visualized.

2.3 2D Image Processing Algorithm

A 2D image processing program has been developed using Matlab (The Mathworks, Inc., R2015a) to address the processing difficulties in bubbly flow image processing. This algorithm consists of four main steps as shown in Fig. 2.4. The pre-processing step aims to enhance the quality of the raw images acquired from high speed cameras to improve the processing accuracy. Two main noise sources, namely, background noise and non-uniform brightness are handled to minimize the error in bubble detection. The second and third step focuses on bubble segmentation for those overlapping bubble clusters. In the second step, the algorithm divides the clustered bubble boundary into separated arcs based on boundary curvature and image intensity gradient information. The third step utilizes topology analysis, which combines the watershed method, bubble skeleton and adaptive threshold method to identify bubble numbers and locations in a cluster. From steps two and three, the separated arcs that belong to the same bubble can be regrouped. In the fourth step, the inner bubble information and ellipse fitting method [51] are used to reconstruct the missing section of each overlapped bubble based on the regrouped arcs obtained from steps two and three. The detailed procedures of the image processing program are discussed in the following sections.

2.3.1 Image Pre-processing

The original high speed images recorded in the experiment come with noises introduced by different factors, e.g., from surface scratches and imperfect machining of the test section. Even with the diffuser, the intensity of the LED light shows certain variations in the imaging plane. Due to lens vignetting effect, brightness will fall off near the corner in high speed images. Thus, pre-processing is necessary to improve the quality of images for further processing.

The recorded high speed images are 8-bit grayscale image and the intensity matrix can be represented by $I_0(x, z)$. As shown in Fig. 2.5 (a), the left and right dark edges are the boundaries of the rectangular channel. The dark lines will be merged with bubbles near the channel boundary while converting a grayscale image to binary image.

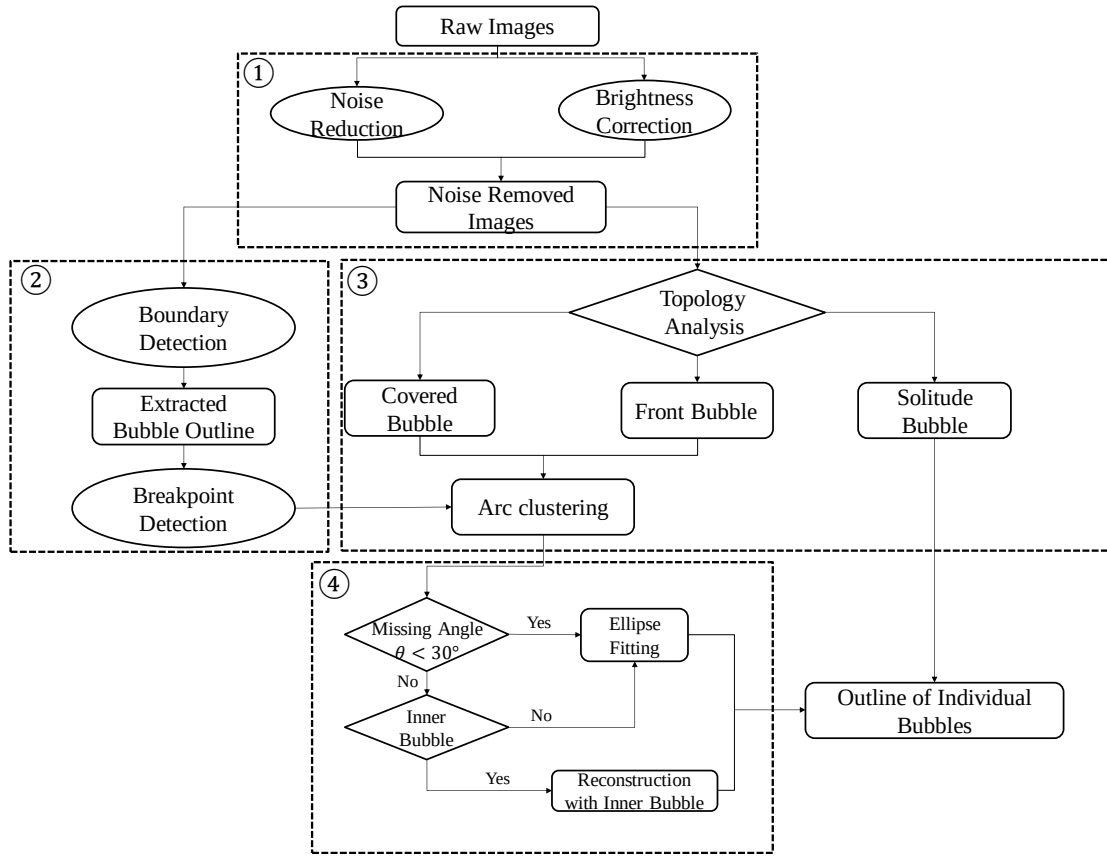


Fig. 2.4 Flowchart of the image processing algorithm. Step 1: pre-processing to remove noise; step 2: outline segmentation based on boundary curvature and image intensity gradient; step 3: bubble number and location identification based on topology analysis; step 4: bubble outline reconstruction.

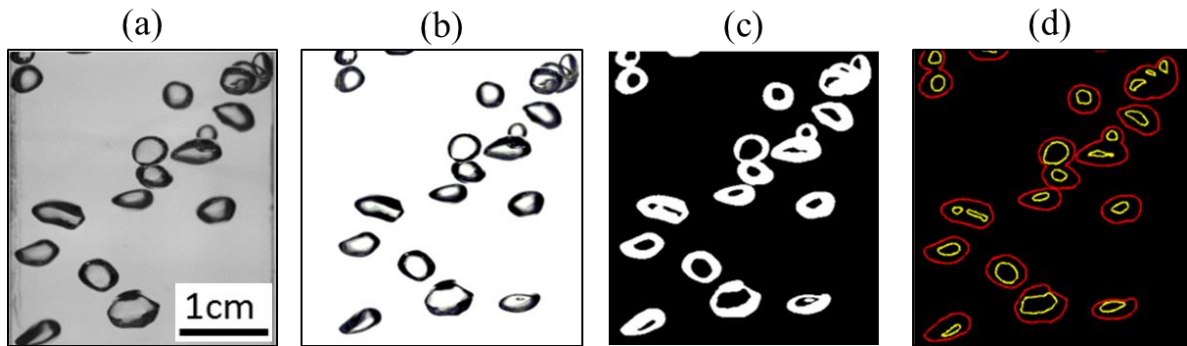


Fig. 2.5 Image pre-processing steps (a) original grayscale image, (b) remove background noise and correct the brightness non-uniformity, (c) convert the grayscale image to binary image based a global threshold, (d) extract the bubble inner boundaries (yellow) and outer boundaries (red).

To eliminate this noise, the background image I_b is taken before each run with water filled in the test section as a reference image for noise elimination. The non-uniform brightness caused by lens vignetting or illumination should be also corrected. This is important as non-uniform background intensity may introduce large uncertainty in the image binarization step to be performed next. In this work, the noise reduction and brightness correction are done by the following equation:

$$I_1 = \underbrace{(I_0 - I_b)}_{\text{Background noise elimination}} - \underbrace{(I_b - I_{avg})}_{\text{Non-uniform brightness correction}}, \quad (2.1)$$

Here, the average image intensity is calculated by:

$$I_{avg} = \sum_{i=1}^N \sum_{j=1}^M \frac{I_b(x_i, z_j)}{MN}, \quad (2.2)$$

where $x_i (i = 1, \dots, N)$, $z_j (j = 1, \dots, M)$ are the coordinates of a pixel. It should be noticed that in the equation, the background noise elimination and non-uniform brightness correction are not limited to directly subtraction operation only. The minus symbol can also represent different noise removal and brightness correction techniques, whichever work best for the bubbly flow images. The high speed image after pre-processing is shown in Fig. 2.5 (b). The dark lines on both left and right boundaries are removed. The contrast between bubbles and the background has been improved. The background brightness also becomes more uniform.

A global threshold is then used to convert the gray scale image to binary image. Fig. 2.5 (c) shows the binary image after removing small objects that are less than 10 pixels. The Canny edge detector is used to acquire the outer and inner boundaries of bubbles for further processing. The red lines in Fig. 2.5 (d) represent the outline of a solitary bubble or the boundary of an overlapping bubble cluster. The inner edge of each bubble shown in yellow is also kept to provide morphological information for the following bubble reconstruction after segmentation.

2.3.2 Outline Segmentation

With the pre-processed images, the next step is to separate the outer boundaries of those overlapping bubbles in a cluster. Fig. 2.6 (a) shows an example of four overlapping bubbles. By visual checking, one can tell the entire outer boundary can be divided into six arcs. The top and bottom bubble contain one arc each. The two bubbles in the middle contain two arcs each. The characters *a-f* are the six breakpoints separating these arcs.

To determine the breakpoints automatically, the boundary curvature and image intensity gradient information are used. Fig. 2.6 (b) shows the curvature calculated for each pixel on the outer boundary. Different color represents different curvature value, increasing from blue to red. The boundary pixels are arranged in anticlockwise sequence, which starts with the leftmost point. For pixels away from a breakpoint, the curve is smooth and the curvature is around 1.5 mm^{-1} , which corresponds to a 3 mm diameter bubble. Near breakpoints, it usually comes with a sharp change in direction and convex curve becomes concave locally. Since the radius around a breakpoint is usually very small, this yields a large negative curvature value. Thus, breakpoints can be detected by searching the local minimum curvature value, which is below a certain threshold along the boundary.

Fig. 2.6 (c) shows the magnitude of the intensity gradient of the same bubble cluster. The outer and inner boundary regions have the largest contrast, which translates into a large intensity gradient value in the image. Overlapping bubbles are located at different depth along the camera optical axis. Therefore, the boundaries show different intensity gradient due to the out-of-focus effect. In Fig. 2.6 (c), bubble 1 and 3 are closer to the camera lens focal plane than bubble 2. It can be seen that the intensity gradient of bubble 2 is smaller compared with the other two bubbles. By checking the intensity gradient distribution, one can distinguish overlapping bubble boundaries according to the intensity gradient value. If there is a sudden change in the intensity gradient, it indicates an overlapping case and the boundary pixels may belong to different bubbles. One can find corresponding breakpoints with a certain threshold of the derivative of intensity gradient.

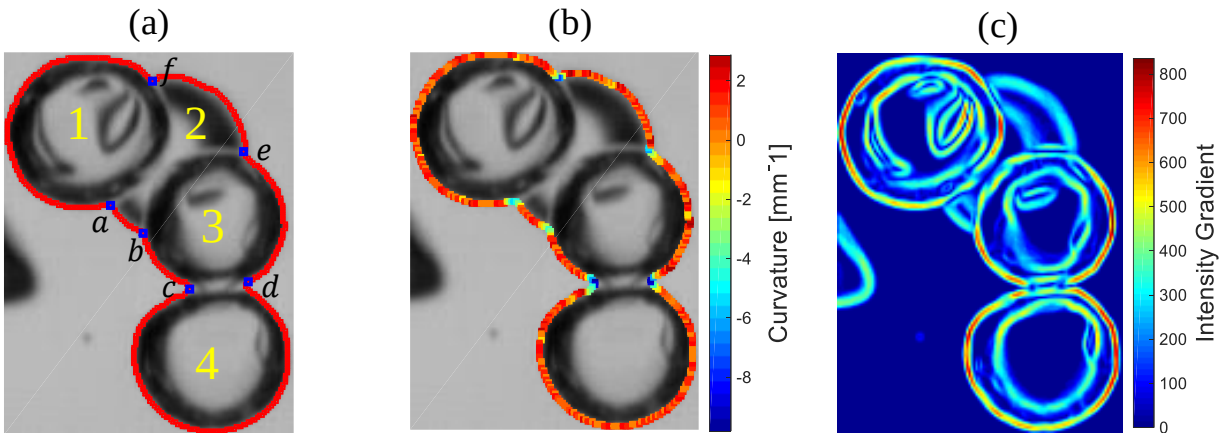


Fig. 2.6 (a) Breakpoints (blue squares) obtained from visual checking in a bubble cluster, (b) curvature distribution around the boundary, (c) intensity gradient of the grayscale image.

In general, the curvature method deals with bubbles with small overlapping area better. Take bubble 3 and 4 in Fig. 2.6 (a) as an example, the boundary has a sharp direction change near the breakpoint c and d . This corresponds to a large negative value below -5 mm^{-1} . In this case, the algorithm has strong confidence in classifying the point as a breakpoint. In some cases, the local negative curvature has an intermediate magnitude. These conditions are ambiguous since it can be a breakpoint with a smoother turn in direction or just part of an irregular shaped bubble. In order to reduce the misclassification rate, these points are identified as possible breakpoints with moderate confidence. Fig. 2.7 (a) shows the identified breakpoints with both strong and moderate confidence from the curvature information.

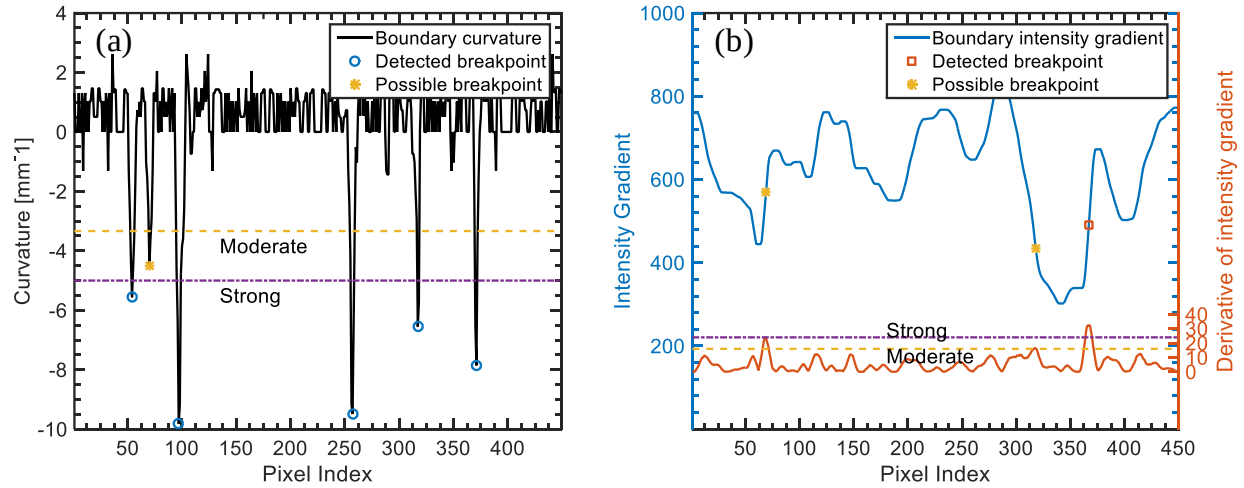


Fig. 2.7 Breakpoint detection of overlapping bubbles based on (a) boundary curvature, and (b) intensity gradient.

The intensity gradient method deals with those bubbles with large overlapping area better. If two bubbles have a large overlapping portion, it indicates that their distance to the camera should be different. Thus, the out-of-focus effect for these bubbles will be stronger which yields a greater change in intensity gradient. By calculating the derivative of the gradient intensity, one threshold can be used to find those corresponding breakpoints in the image. Following the same strategy used in the curvature method, those points meet a high threshold are classified as breakpoints with strong confidence. The possible breakpoints are labeled with moderate confidence. Then the final decision on whether a pixel on the boundary should be labeled as a breakpoint or not is made by combining these two methods together according to Table 2.2. If either the curvature or intensity

gradient method has strong confidence, this pixel will be labeled as a breakpoint. If both the curvature and intensity gradient method have moderate confidence, the pixel will also be labeled as a breakpoint. Otherwise, the pixel will not be identified as a breakpoint.

Table 2.2 Decision table for outline segmentation using the boundary curvature and intensity gradient information.

No.	Curvature	Intensity gradient	Breakpoint
1	Strong	-	✓
2	-	Strong	✓
3	Moderate	Moderate	✓
4	Moderate	Weak	✗
5	Weak	Moderate	✗

By combining the two methods together, the accuracy of identifying the breakpoint in a cluster can be significantly improved. Fig. 2.8 shows several examples of using the outline segmentation algorithm to separate the clustered bubble boundaries. The breakpoints detected by the curvature method with strong confidence is highlighted by blue circles. The breakpoints detected by intensity gradient change with strong confidence is highlighted by red squares. The breakpoints detected by both curvature and intensity gradient with moderate confidence are marked with yellow asterisks. The first example is a cluster with three bubbles together. For the bubble on the left, the bottom breakpoint is detected by both methods. The top breakpoint is detected by combining both methods with intermediate thresholds. In the intensity gradient plot, there are five possible breakpoints. Three of them have been confirmed by the curvature method with strong or moderate confidence. The other two points are actually caused by the fluctuation of intensity along the bubble edge. These two undesired points are eliminated in the final result by the algorithm.

The second example shows two bubbles with a large overlapping portion. In this case, most part of the smaller bubble on the front side overlaps with a large bubble on the back side. The boundary near the breakpoints is relatively smooth and has no obvious change in direction. The curvature method only indicates one possible breakpoint. The intensity gradient method works

well for this condition since the bubble distances to the high speed camera are quite different. The algorithm is able to detect two breakpoints with strong confidence and separate the boundary correctly. The third example is a case with a large group of bubbles clustered together. The breakpoints can be identified accurately with the proposed method in such a complex scenario. The only point which is not detected correctly is located at the top-left corner, where the bubble shape is influenced by the test section wall. However, this over segmentation will not cause uncertainty in the final result as the two separated arcs will be regrouped together in the following arc clustering step.

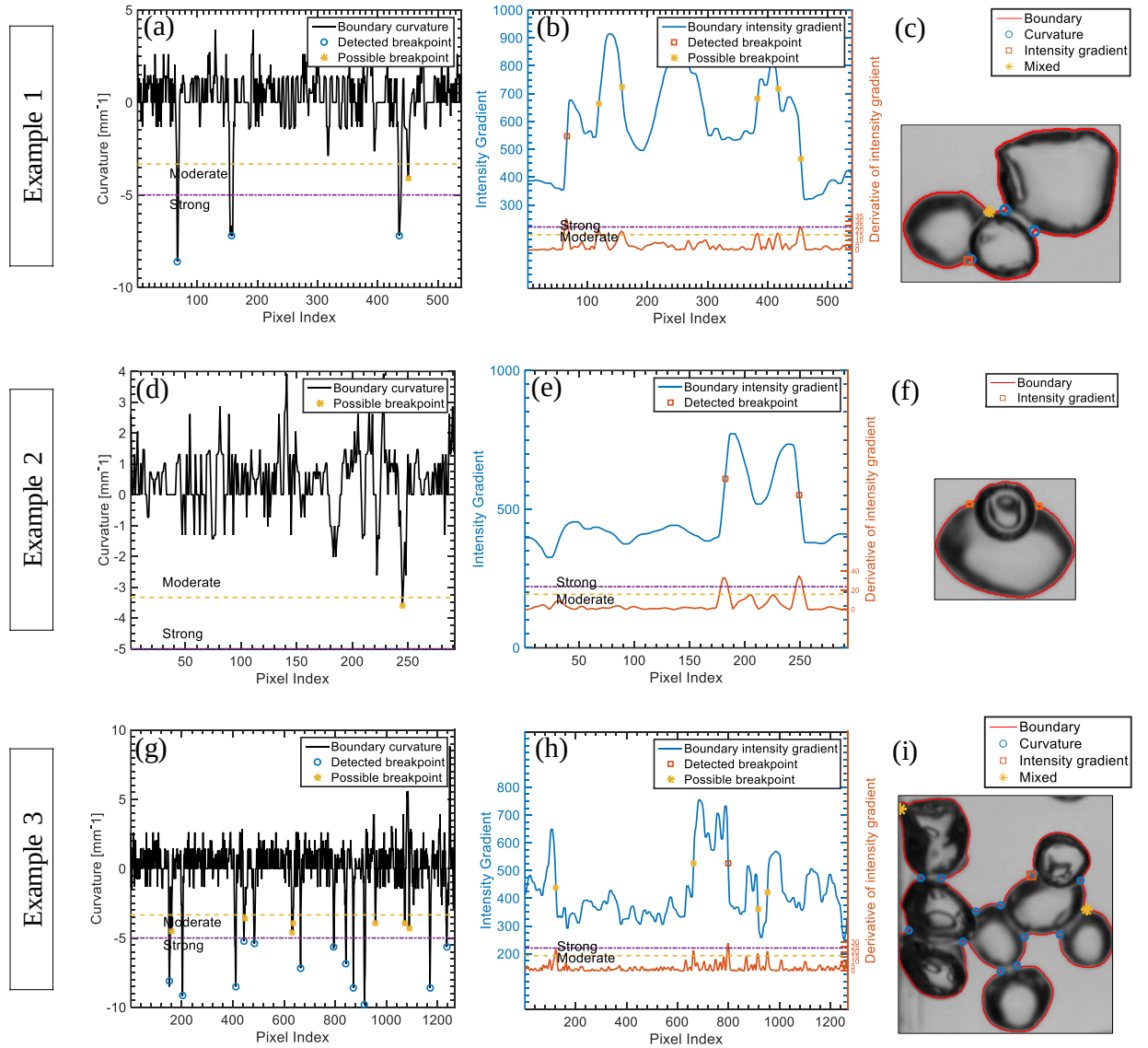


Fig. 2.8 Examples showing the breakpoint detection algorithm based on combined curvature and intensity gradient information.

2.3.3 Topology Analysis

The separated boundary arcs that belong to the same bubble should be regrouped together for the following processing. In the literature, watershed method is a commonly used method to separate the bubbles in a cluster and has a reasonable computational efficiency. But it has limitations as discussed earlier since it separates the cluster based only on the boundary shape. To overcome the shortcomings of the watershed method, additional geometry and intensity information are extracted and combined together for the determination of the right number of bubbles in a cluster.

Fig. 2.9 shows the three methods used in counting the bubble number. The watershed segmentation is used as a reference since it preserves the outer boundary of a cluster. To utilize information from the inner region of a cluster, a “bubble skeleton” is obtained from the original image. For a bubble with a smooth surface, the image shows a dark edge and a bright inner region. After converting the grayscale image to binary image, the bubble edge becomes a white band with a certain thickness. The white band is then narrowed to a white curve based on the intensity gradient information. The gradient direction on the band is first calculated, and only the pixel with a local maximum in this direction is kept for the skeleton. Fig. 2.9 (c) shows the obtained bubble skeleton from the original image. The bubble number in the cluster can be obtained by counting the connected holes in the skeleton image.

Fig. 2.9 (d) is obtained by applying an adaptive threshold method [52] to the grayscale image. During binarization processing, a global threshold can separate the background and the bubbles efficiently. However, it cannot separate single bubbles in a cluster since the intensity changes between bubbles are much smaller compared to the intensity difference between background and bubbles. By the visual operation, the shape of the front bubbles in an overlapping cluster are well recorded in the grayscale image. To extract these front bubbles, an adaptive threshold method is used. The main idea of the adaptive threshold method is similar to the global threshold method, but the threshold is chosen differently for each pixel according to the intensity distribution in the nearby region. This method is more sensitive to the intensity changes and thus can effectively separate the front bubbles from the cluster. In this work, an 11×11 window is selected for each pixel. Then a local threshold within this window is calculated to perform binarization. With this method, those front bubbles which are not covered appear as a connected ring shape with all edge pixels identified. The covered bubbles usually appear as segmented arcs in the image. In Fig.

2.9 (d), it shows that three front bubbles are completely extracted from the cluster based on the adaptive method. In the adaptive threshold method, only the detected front bubbles with all edge pixels identified are counted.

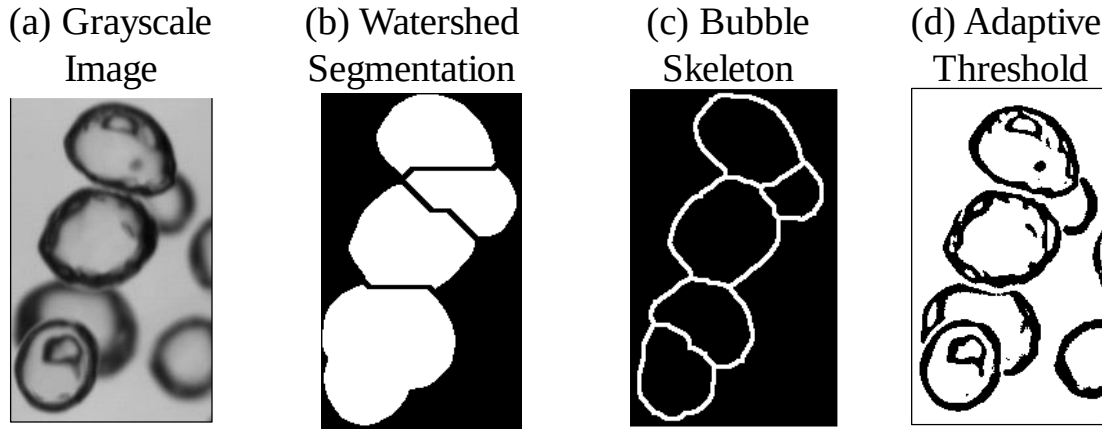


Fig. 2.9 Obtain bubble number in a cluster, (a) original grayscale image, (b) watershed segmentation method, (c) bubble skeleton, (d) adaptive threshold method.

In order to identify the bubble number correctly, the three methods discussed above are integrated according to a flowchart shown in Fig. 2.10. The basic idea is to use the watershed method as a reference to determine bubble number. Information obtained from the bubble skeleton and adaptive threshold result will be used to make any corrections when necessary. The watershed method is used as a reference because it not only contains bubble number information but also preserves the outer boundary. Resulting images from the other two methods may have a slight shift from the original image. The bubble skeleton method shrinks edges and the skeleton is located at the center of the band. In the adaptive threshold method, the final edge location may differ from that obtained from the global threshold method, as the threshold used for each pixel is determined locally. Though bubble boundary has been slightly distorted, both the skeleton and adaptive threshold methods are good indicators for bubble number. Thus, these two methods are used to correct the bubble number obtained by the watershed method. In the algorithm, each connected block based on watershed method are compared with the other two methods in the same area. For each block, the projection area is denoted as A_r . Following the flowchart shown in Fig. 2.10, the bubble number in the corresponding area is examined by bubble skeleton and adaptive threshold

method in sequence. By checking all the separated binary large objects (blobs) in a cluster based on the watershed method, the final bubble number can be decided accordingly. In this flowchart, each circle stands for one individual bubble detected by the method indicated in the first element of the row. The factors in front of A_r , 0.5 and 2, respectively indicate an under- and over-segmentation by the watershed method. They do not indicate the actual projection area of the blob.

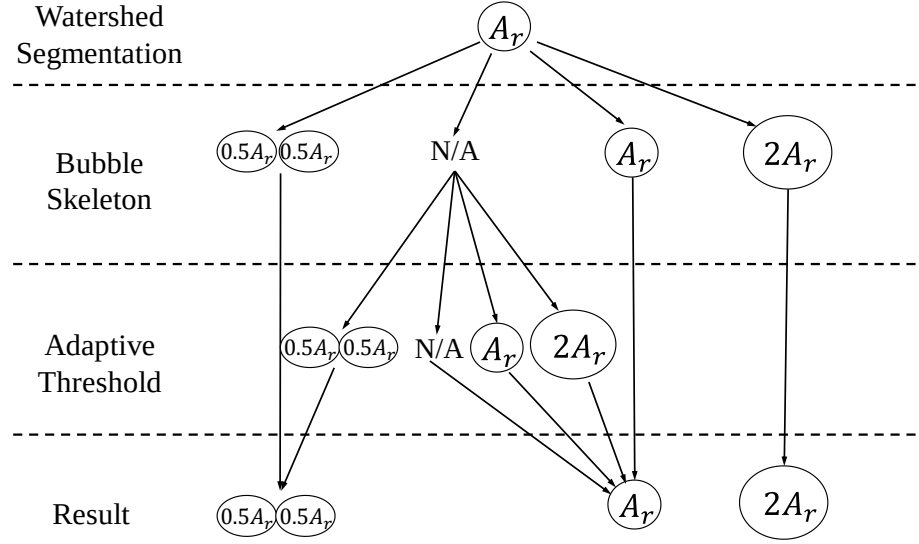


Fig. 2.10 Flow chart to determine bubble number. Each detected blob from watershed segmentation method is denoted as A_r . The same blob region is checked by bubble skeleton and adaptive threshold method. The factors in front of A_r , 0.5 and 2, respectively indicate an under- and over- segmentation by watershed method. The final output bubble number is listed in the fourth row for different conditions.

Fig. 2.11 shows four examples of using the above flowchart to decide bubble number in a cluster. In the first example, two bubbles near the bottom are grouped as one blob according to the watershed method. Following the algorithm, this blob is given an area A_r . Checking the same interested area, the bubble skeleton method tells that there are two smaller bubbles, each indicated by an area $0.5A_r$. The adaptive threshold result is examined next. It tells that one smaller foreground bubble, indicated by $0.5A_r$, is completely detected with all edge pixels being identified. As can be seen in the grayscale image, another bubble in this area is partially covered by the front bubble. Thus, the shape of this bubble cannot be completely extracted by the adaptive threshold method.

Combine three methods together, one can decide that there are two smaller bubbles in this area and the watershed method has under-predicted the bubbles number.

For the second example, an elongated bubble is divided into two parts by the watershed method. In the algorithm, these two parts will be examined by the other two methods. Use the blob highlighted in the red dashed box as an example, the area is denoted as A_r again. The bubble skeleton indicates that the bubble is much bigger than the watershed prediction in the same area, assigning it an area $2A_r$. For the adaptive threshold method, the detected bubble is not complete since its top part is covered by another bubble. The area information is not available (N/A) in this case. Using the flowchart, one can decide that the watershed method has over-estimated the bubble number, and the bottom two blobs should belong to the same bubble.

The third example shows a case which contains a large bubble in a cluster. Due to the effect of surface deformation, the large bubble has a much darker center region. The watershed method is based on the object geometry information. Thus, the large bubble can still be separated and labeled with A_r by the watershed method. The bubble number information is not available (N/A) from bubble skeleton method in this case since the bubble has no clear edge with a bright center region. Follow the flow chart in Fig. 2.10, the region is further checked by the adaptive threshold method. It can be seen that the large bubble is detected with a connected edge in the image. In this case, the bubble number is identified as one in the red dashed box when the bubble skeleton information is not available.

The fourth example shows a large cluster containing eight bubbles. Based on the watershed method, the eight separated blobs are checked in sequence using the flow chart. With the proposed method, the algorithm shows the ability to handle those large bubble clusters with complicated topology structure.

From the above examples, it is seen that the watershed method in example 1 and 2, the skeleton method in example 3, and the adaptive threshold method in example 2 and 4, all show certain errors or deficiencies in counting bubble number individually. But combining these methods according to the proposed flowchart, these errors have been corrected successfully, which results in an accurate bubble count in all four examples. The blobs from the watershed method can be merged or divided to reflect the corrected bubble number. Since the outer boundary of the blobs obtained from the watershed method is unchanged, one can match the separated arcs from step two (Section 2.3.2) to these corrected blobs to find all the outline arcs for each individual bubble.

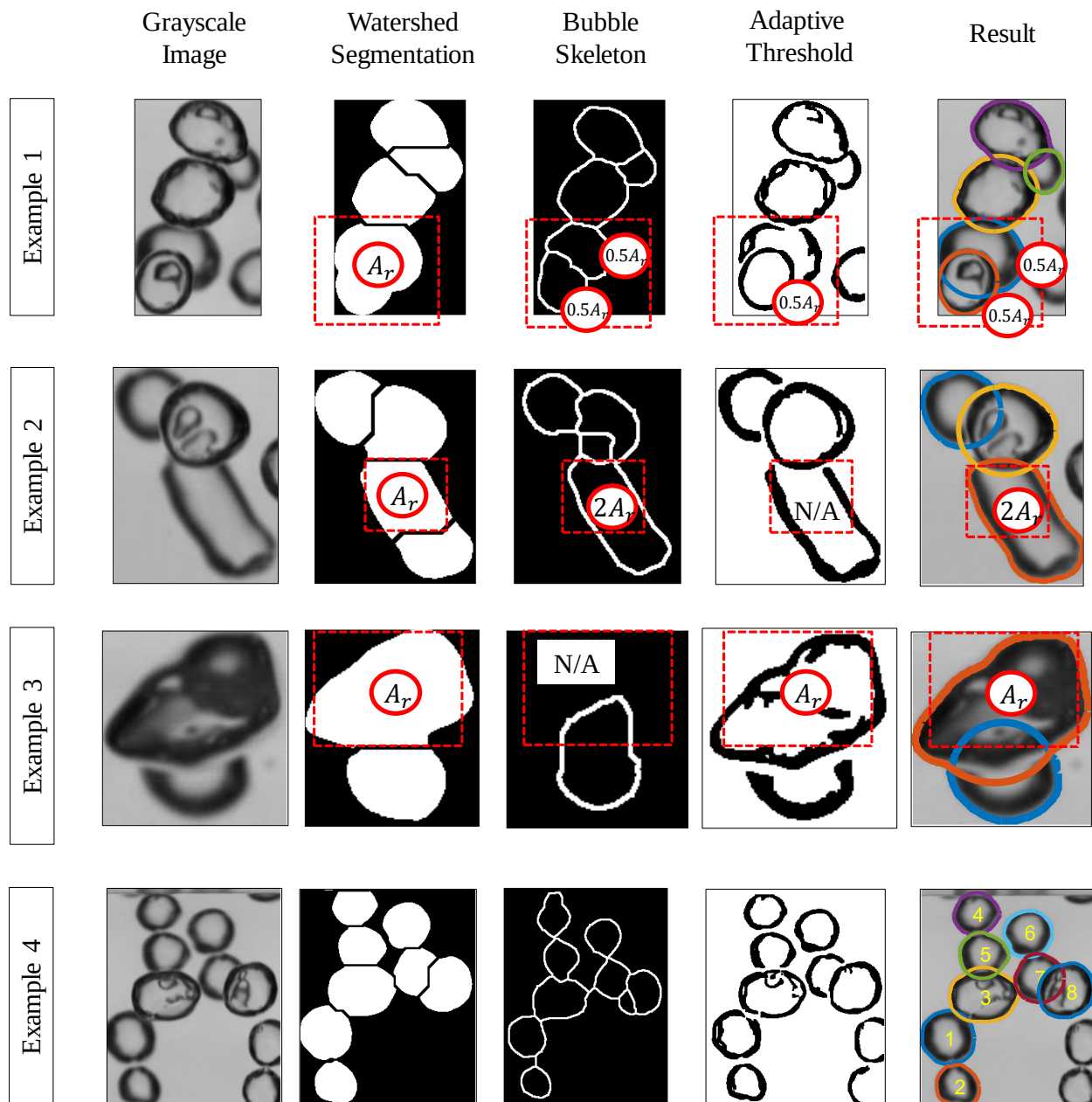


Fig. 2.11 Examples of determining bubble number using the flowchart shown in Fig. 2.10. Example 1: overlapped bubbles where the watershed method under-estimates the bubble number; Example 2: an elongated bubble where the watershed method over-estimates the bubble number; Example 3: a dark bubble with surface deformation where bubble skeleton method is not available; Example 4: an example of determining bubble number in a large cluster.

2.3.4 Bubble Outline Reconstruction

After arcs are matched to bubbles in a cluster, the next step is to reconstruct the missing parts for each bubble. An ellipse is first fitted to each bubble using the available arcs to determine the angle of a missing section. If the missing section angle is smaller than 30° , the ellipse fitting method will be used to fill the missing section. If the missing section angle is larger than 30° , the existence of an inner bubble (inner edge) will be examined first. If the inner bubble is similar to the outer boundary, the inner bubble will be moved to the center of the outer boundary and enlarged to complete the missing section. If there is no corresponding inner bubble or the inner bubble is distorted, ellipse fitting will be used. A reconstruction of three overlapping bubbles in a cluster is shown in Fig. 2.12 as an example. With the bubble segmentation algorithm described above, the cluster boundary is divided into four arcs and matched to the three bubbles in this cluster. In this case, all the three bubbles have clear inner bubbles. For bubble 1 and 2, the detected missing sections are larger than 30° . The corresponding inner bubbles are enlarged to connect the missing sections. For bubble 3, the angle of the missing section is 28° . Thus, ellipse fitting is used directly to connect the missing section. The reconstructed outlines of each individual bubble were plotted on the original grayscale image in Fig. 2.12 (c). As can be seen in the figure, the unoccluded bubble boundaries are kept and the reconstructed missing sections show a good match for each individual bubbles.

Fig. 2.13 shows three sample results of typical bubbly flow images obtained using the above image processing algorithm. Each single bubble detected by the algorithm is marked by their reconstructed outlines shown in different colors. By visual observation, most bubbles, either solitude or clustered, are correctly identified by the algorithm. The overlapping, irregular shape and deformation problems are handled properly so that reconstructed outlines show good accuracy.

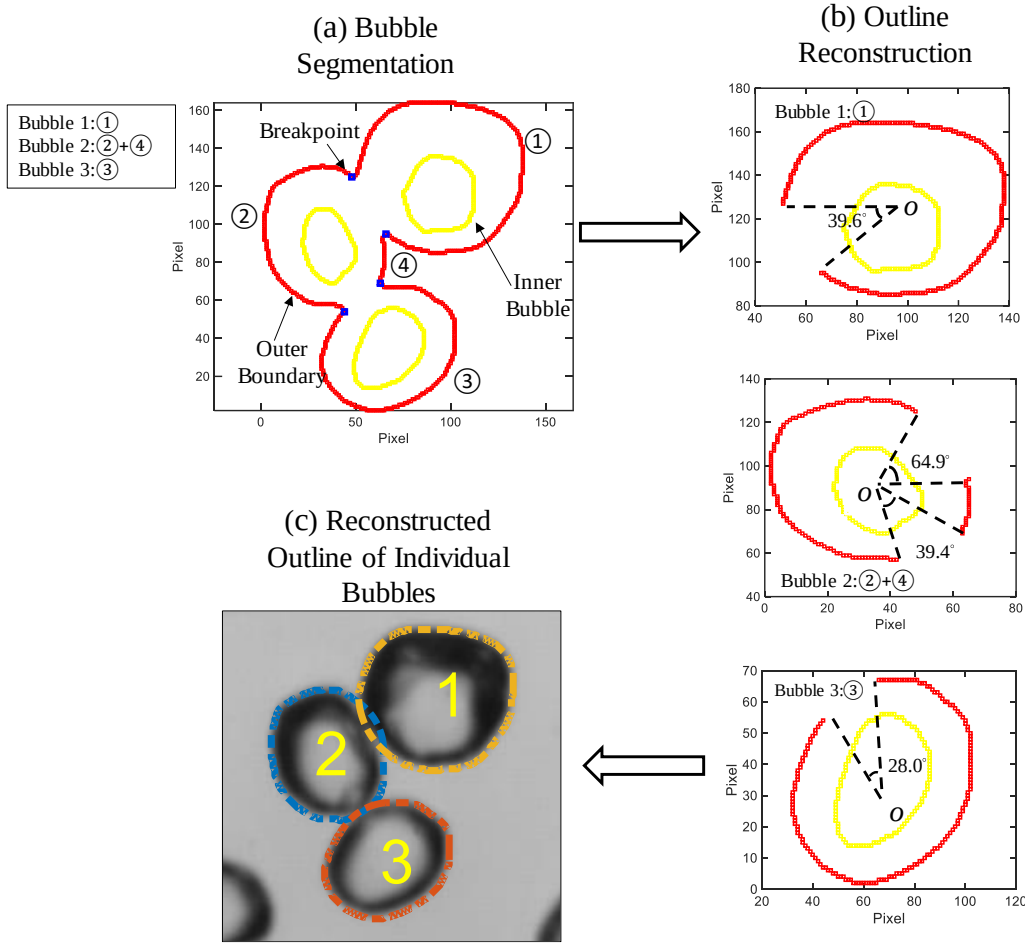


Fig. 2.12 Reconstruction of individual bubble outlines in a cluster (a) bubble segmentation results obtained from Section 2.3.2 and 2.3.3, (b) bubble reconstruction with inner bubble and ellipse fitting, (c) the reconstructed outline of each separated bubble.

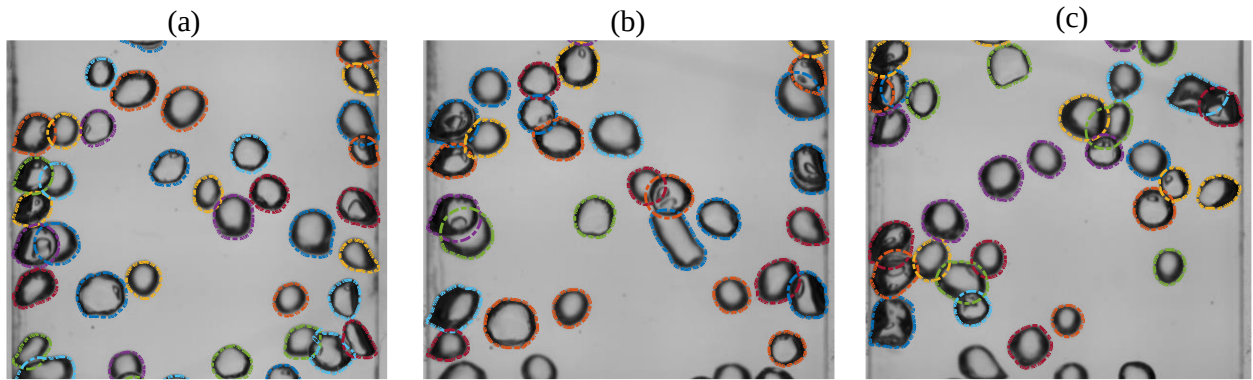


Fig. 2.13 Sample results of reconstructed bubble outline for typical bubbly flows. The reconstructed outlines are plotted on top of the grayscale image for visual comparison.

2.4 Algorithm Benchmark with Synthetic Images

To quantify the uncertainty of the proposed 2D image processing algorithm in this chapter, synthetic images are generated in a simulated test section with the same geometry as the experiment setup for benchmarking purpose. Synthetic bubbles are generated based on an ellipsoid model, which can be described by three semi-axes $(a_{x,i}, b_{y,i}, c_{z,i})$. In addition, three Euler angles $(\alpha_i, \beta_i, \gamma_i)$ should be used to account for the rotation of each bubble. The subscript i represents the i^{th} bubble in the synthetic image. To simplify the problem in this study, semi-axis $c_{z,i}$ is set as the shorter one among $a_{x,i}$ and $b_{y,i}$. Also, bubbles are allowed to rotate only around the y axis, which translates into $(\frac{\pi}{2}, \beta_i, -\frac{\pi}{2})$ in the Euler angle system. The synthetic bubbles generated this way make it possible to calculate the bubble volume once the outline is correctly identified. Therefore, the void fraction can be determined accurately based on images obtained from a single camera. This provides useful information on the void fraction range the developed algorithm can be confidently applied to.

The rotation angle β_i along the y axis is generated randomly in the range of $[-\frac{\pi}{2}, \frac{\pi}{2}]$. The semi-axes $a_{x,i}$ and $b_{y,i}$ have the same mean value r_{avg} . Each has a rectangular distribution with a 0.5 mm width. The center locations of individual bubbles (x_i, y_i, z_i) are assigned randomly in the simulated test channel. Algorithms have been implemented to prevent the violation of geometrical restrictions, namely, no bubble should cross the wall boundaries and bubbles are not physically overlapping with one another.

In this test, synthetic images are generated with the void fraction of $\alpha = 0.02, 0.05, 0.08, 0.10, 0.12, 0.15$ and 0.18 for different $r_{avg} = 1.5 \text{ mm}, 2.0 \text{ mm}$ and 2.5 mm . Each condition consists of 100 frames, and the results are obtained by averaging over all frames. Fig. 2.14 shows a sample frame of random generated synthetic bubbles in the test section. The color of the bubble denotes the volume equivalent diameter varying from 2 mm to 4 mm. Larger bubbles are shown in yellow and smaller ones are shown in blue.

With the generated 3D images, the bubbles are projected to the x - z plane to simulate the images acquired from the high speed cameras. Fig. 2.15 shows the steps by converting generated 3D ellipsoid bubbles to a 2D ellipse in image. First, two templates of bubble projections are

generated to account for the out of focus effect. The image intensity across a bubble edge is given a Gaussian distribution. The background intensity is set as the average background intensity in high speed images in the experiment. When two bubbles are overlapping, one will be further away from the focal plane than the other. This bubble is given a smoother intensity change (or larger standard deviation in Gaussian) on edge, whereas the other bubble has a shaper edge (or smaller standard deviation) as can be seen in the figure. The projected 2D ellipse in the imaging plane can be determined using the semi-axes and rotation angle information. Then one of the templates are stretched and rotated so that it can be mapped to the 2D ellipse. Without loss of generality, the focal plane in this synthetic bubble test is assumed to be within $0\text{mm} \leq y \leq 5\text{mm}$ range. If the bubble center value y_i is in this range, the shaper template will be used, otherwise, the softer one will be used. Repeating this procedure for all the bubbles in one frame, the final synthetic bubble images can be obtained as shown in Fig. 2.15. It can be seen that the synthetic image contains random bubbles with different sizes and rotation angles. The out-of-focus effect, and bubble clustering and overlapping are also well reproduced in the image. The spatial resolution of the image is 20 pixels per mm, which is similar to the experimental images.

The synthetic images are processed by the image processing algorithm described in Section 2.3. The time-averaged information of bubble number density can be calculated after individual bubbles are extracted from the images. Fig. 2.16 shows the relative number density errors of the image processing results. It can be seen that number density is under-estimated for all conditions due to the overlapping problem. The number density error increases with increasing void fraction and with decreasing bubble size. Since number density is higher for the smaller bubble at a fixed void fraction, small bubble size may cause more bubble overlapping problem which may explain the error trend shown in the plot. When void fraction is below 10%, the number density errors are below 5% for the all bubble sizes tested. Above 10%, a rapid increase of relative errors is seen for $r_{avg} = 1.5$ and 2.0 mm. For a larger bubble size of $r_{avg} = 2.5$ mm, the error is -2.029% even at a high void fraction $\alpha = 0.18$. This synthetic bubble test result shows that the developed algorithm has a robust performance within 10% void fraction for bubble sizes of practical interest. For void fraction higher than 10%, the algorithm can still produce an accurate result for larger bubbles. However, special attention should be paid when applying the algorithm to smaller bubbles as the errors may be significant.

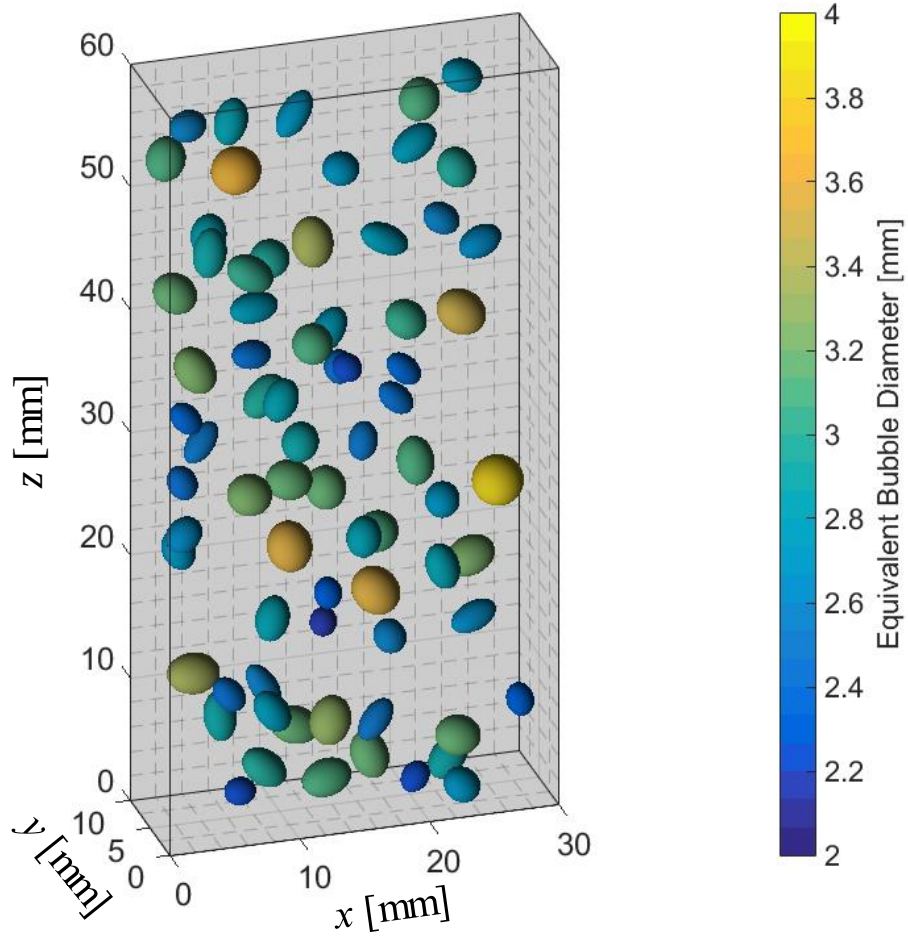


Fig. 2.14 Randomly distributed ellipsoid bubbles in a volume that has the same cross section as the actual test facility (30 mm $\times$ 10 mm). The case shown in the figure has a void fraction $\alpha = 0.05$, mean semi-axis $r_{avg} = 1.5$ mm. The color of the bubble indicates the equivalent bubble diameter.

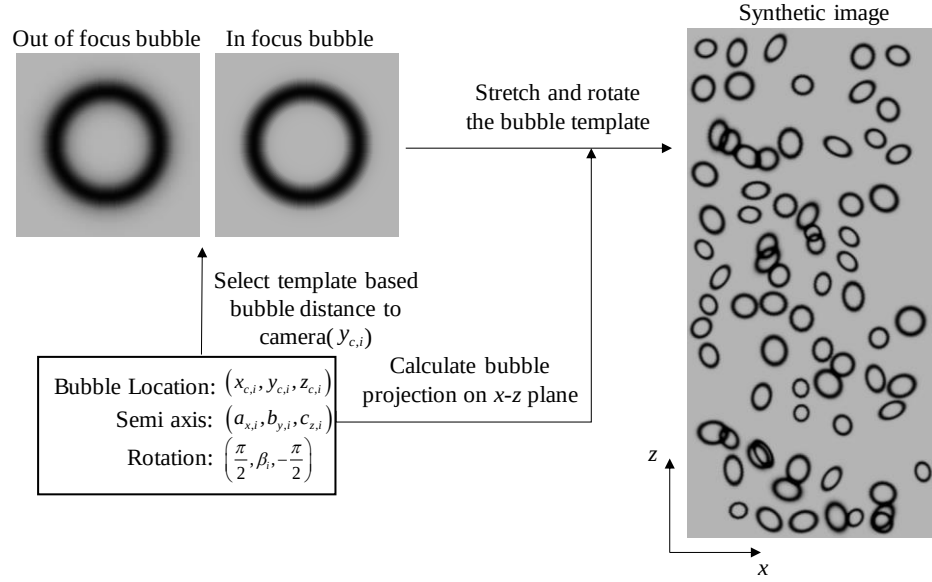


Fig. 2.15 Procedure to obtain synthetic bubble image with out-of-focus effect. Bubbles, which are slightly out-of-focus, show a higher degree of Gaussian blur.

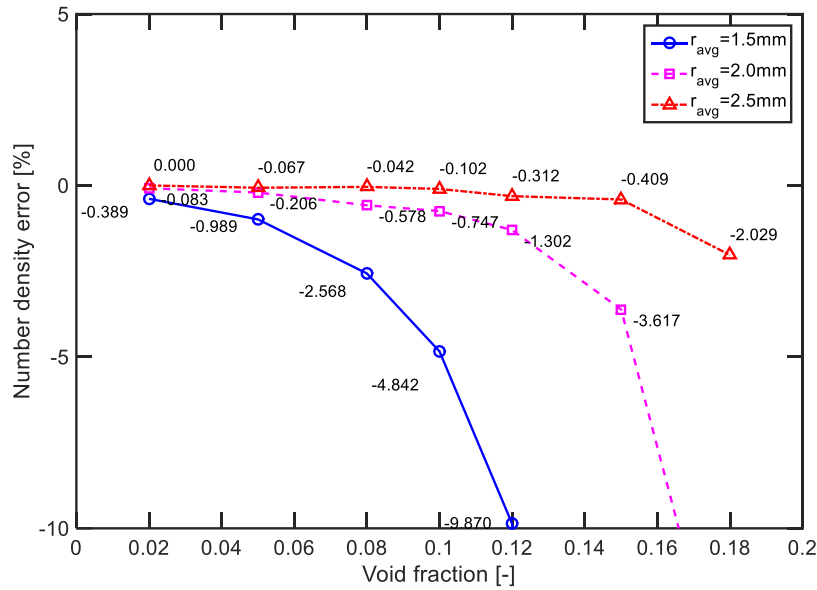


Fig. 2.16 Number density error varying with void fraction for three mean semi-axis values: 1.5, 2.0 and 2.5 mm. The number next to a marker shows its relative error.

2.5 Summary

A robust 2D image processing algorithm has been developed for bubbly flow measurement. Both bubble segmentation and reconstruction techniques are discussed in detail in this chapter. The algorithm combines the geometrical, optical and topological information obtained in the high speed images. It is capable of resolving the image processing challenges commonly found in similar applications. A synthetic bubble image test is performed to verify the developed algorithm, and further quantify the measurement uncertainty under various conditions. It shows that the algorithm has a high accuracy in number density measurement for large bubbles at void fraction up to 18%. The relative number density error increases with decreasing bubble size, but still below 5% at void fraction 10% or lower.

The outline reconstruction has also been improved compared to simple ellipse fitting method widely used in the literature. An accurate outline is necessary for 3D bubble reconstruction, and bubble volume and surface area measurement. These values are essential to obtain the parameters of practical interest such as void fraction and interfacial area concentration. If individual bubbles are not measured properly, the final time- and space-averaged data may contain large uncertainty. However, more than one camera is required to accurately measure the volume and surface area of individual bubbles. Study on reconstructing 3D bubble based on the 2D bubble information obtained by the presented algorithm will be reported in Chapter 4.

3 Study of Bubbly Flow Characteristics

This chapter studies the characteristics of the bubbly flow in the rectangular channel with a cross-section of 30 mm $\times$ 10 mm. Eight bubbly flow runs are recorded with three synchronized high speed cameras. The recorded images are processed with the 2D image processing algorithms developed in Chapter 2. The distribution of bubbly flow void fraction, interfacial area concentration, bubble Sauter mean diameter, etc., are reported both in the axial and transverse directions. The acquired experiment data are used for the benchmarking of the interfacial area transport equation and bubble number density transport equation.

3.1 Experimental Conditions

Eight test runs with different superficial gas and liquid velocities are performed in this chapter as shown in Fig. 3.1, where the bubbly-to-slug transition line is given by Mishima and Ishii [53]. The superficial gas velocities are fixed at 0.05 m/s (run 5-8) and 0.01 m/s (run 1-4) with superficial liquid velocity ranging from 0.50 to 2.12 m/s. The maximum local void fraction in these runs could reach 17%. The fluid temperature is maintained at 28 ± 1.2 °C during the test.

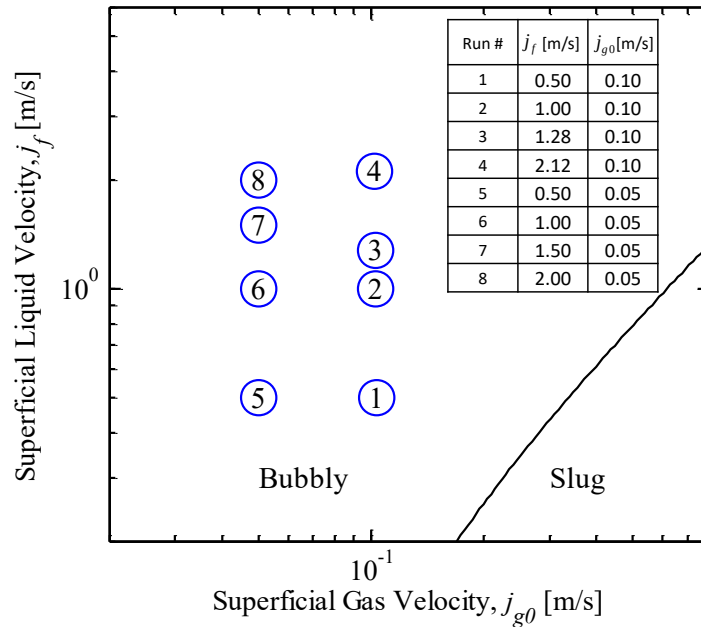


Fig. 3.1 Test conditions in a j_g - j_f map.

Two high-speed cameras (Photron FASTCAM SA4) are used to take images at the first and second visualization port ($z/D_h = 8.8$ and 72.4). The resulting images have the resolution of 0.065 mm per pixel. Another high-speed camera (Photron FASTCAM SA6) is placed at the third port ($z/D_h = 136$) to take images at the resolution of 0.043 mm per pixel. With such resolutions, a 3 mm bubble contains at least 1650 pixels in the image. All images are taken from the 30 mm wall side. Three LED panels are arranged in a backlight configuration to provide a uniformly illuminated background. At each port, the recorded images correspond to a 30 mm (width) by 60 mm (height) flow region. All three cameras are synchronized at the frame rate of 1000 frames per second. Ten seconds of data are taken for each run, which results in 10000 sequential images at each port.

Sample bubbly flow images for run 1-4 are shown in Fig. 3.2. Checking visually, one can identify some common trends in the upward bubbly flow. From port 1 to port 3, the bubbly size will increase and the bubbly number density usually will decrease accordingly. From run 1 to run 4, the superficial liquid velocity increases from 0.5 m/s to 2.12 m/s, this results in a decrease of bubble size. For run 5-8, similar trends can be found in Fig. 3.3. The superficial gas velocity $j_{g0} = 0.05$ m/s in run 5-8 is only half of the $j_{g0} = 0.10$ m/s used in run 1-4. This results in a significant bubble number density decrease in run 5-8 with similar j_f setup. By visual check, the bubbly flow characteristic can only be analyzed qualitatively. The quantitative information of bubbly flow void fraction, interfacial area concentration and bubbly number density distribution require the utilization of the 2D image processing techniques, which will be reported in the following sections.

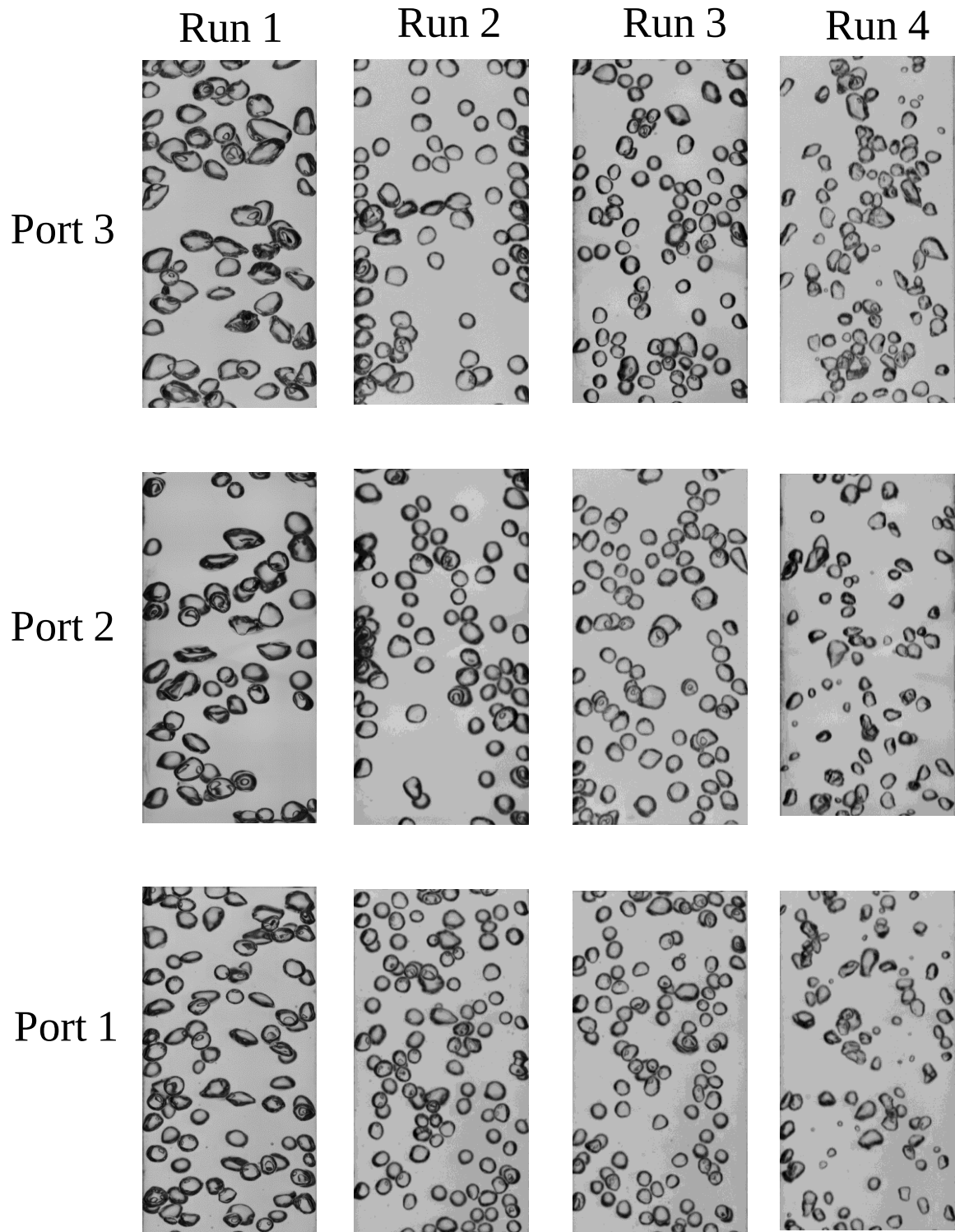


Fig. 3.2 Sample high speed images for bubbly flow run 1 to run 4 at three visualization ports.

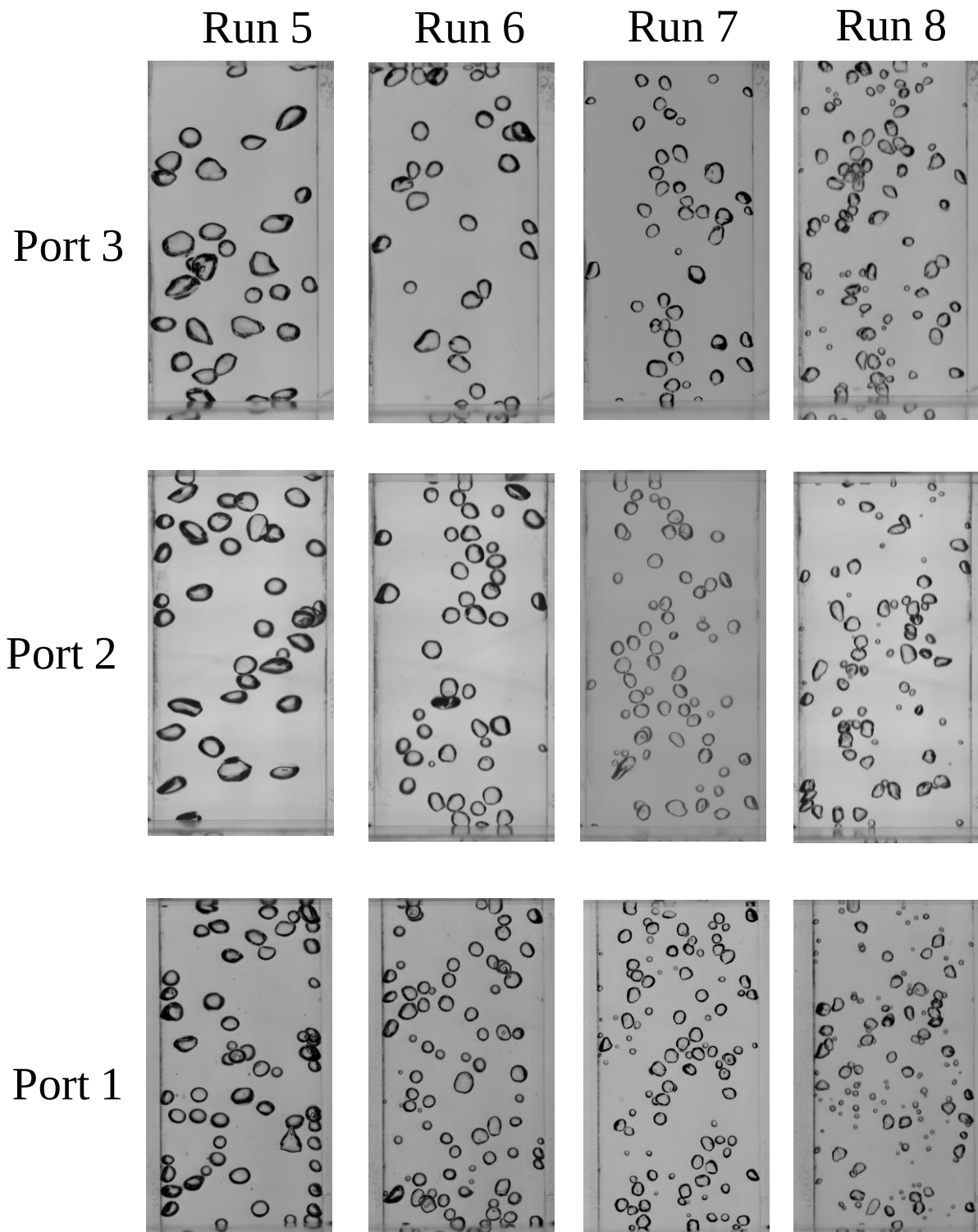


Fig. 3.3 Sample high speed images for bubbly flow run 5 to run 8 at three visualization ports.

3.2 Results Comparison with Flow Meters and Conductivity Probe

In Fig. 3.4, the superficial gas velocities obtained by the 2D image processing algorithm are compared with those obtained from the gas flow meters and local pressure measurements at three different ports. The mean absolute relative error is 11%, with the highest error of 21%. The discrepancies seem to be randomly distributed among different runs, which rules out a systematic over- or under-prediction by the image processing technique.

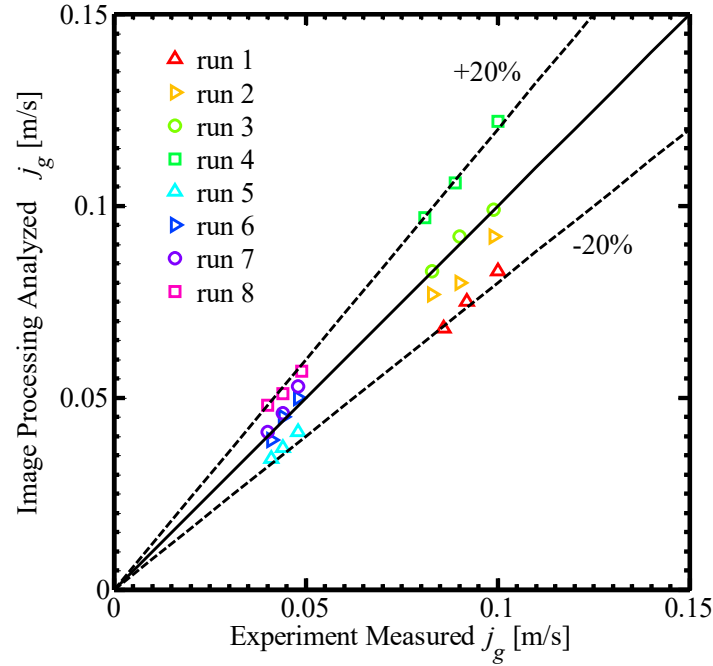


Fig. 3.4 Comparison of j_g measured by image processing method and gas flow meters.

To determine the accuracy of the 2D image processing scheme in obtaining the local two-phase flow quantities and their distributions in the transverse direction, a benchmarking study is carried out using the double-sensor conductivity probe. A schematic of the test setup is shown in Fig. 3.5. The double-sensor conductivity probe is placed on a two way linear stage. By adjusting the micrometers mounted on the linear stage, the probe can be moved to a designated location in the test section. Probe measurement is performed at 94 locations covering the entire cross section at the third port ($z/D_h = 136$). A data acquisition system is used to convert the analog voltage signal

from the probe to digital signal. The two-phase flow parameters such as void fraction and bubble velocity are then obtained by processing the digital signals by a single processing program. The probe signals are sampled for 180-270 s at each location to ensure that enough bubbles are obtained for computing the time-averaged parameters. At each specific x location, nine corresponding points in the y direction are measured by the probe. From these local measurements, the line-averaged parameters along the 10 mm gap can be calculated and be compared with the image processing results.

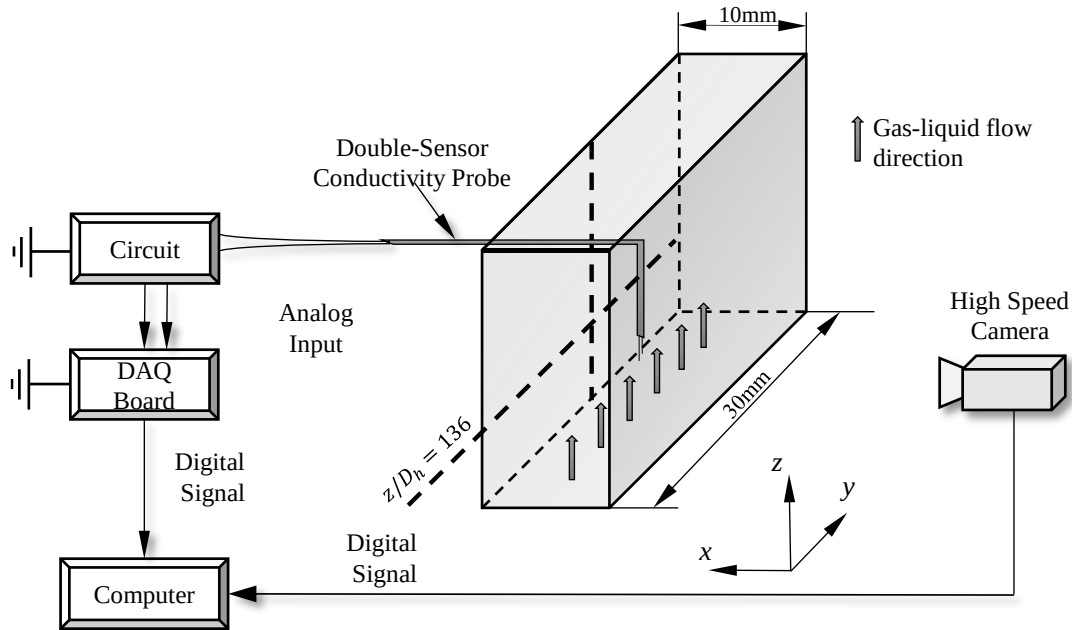


Fig. 3.5 Configuration of the double-sensor conductivity probe and high speed camera for the benchmarking test at $z/D_h = 136$.

Fig. 3.6 shows the line-averaged void fraction and velocity distributions in the transverse direction (along x) at the third port for run 7. The data obtained from high speed images are compared with that obtained from the double-sensor conductivity probe. As can be seen from the figure, the image data appear as continuous curves spanning the entire 30 mm wide test section due to its high resolution. Whereas the probe data can be taken only at limited discrete locations. The relative errors of void fraction are within $\pm 10\%$ except for the points near the wall boundary. It should be noted that the uncertainty in the probe data may also increase near the wall due to the increased flow disturbance by the probe. The velocity compares well with the probe data with the relative error less $\pm 10\%$ for all the measurement locations. These results show that the imaging

processing scheme has a good measurement accuracy for the bubbly flows tested in this experiment.

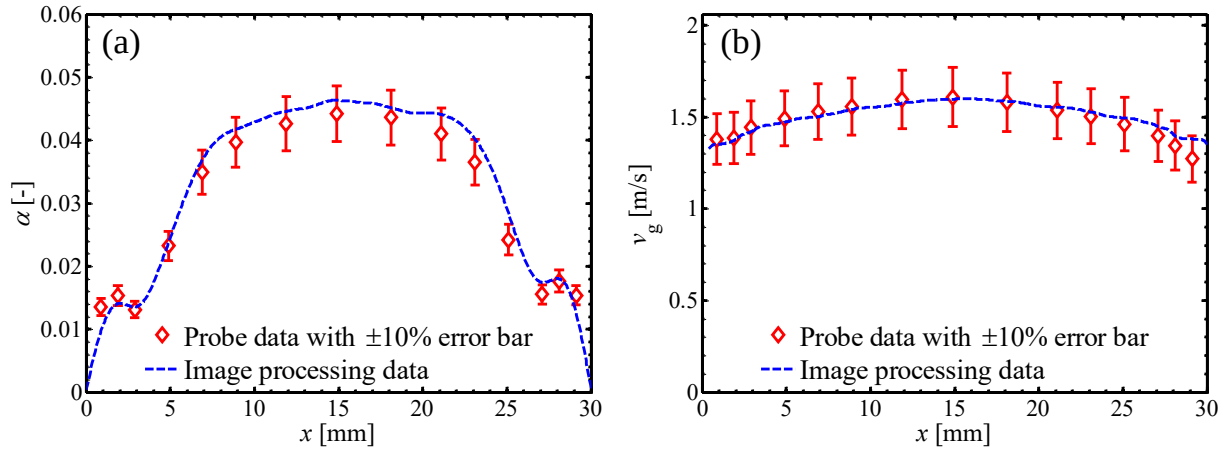


Fig. 3.6 Comparison of image processing method and double-sensor probe for run 7, a) void fraction distribution along x , b) bubble velocity distribution along x .

3.3 Analysis of Bubbly Flow Characteristics

3.3.1 Distribution Along the Transverse Direction

Fig. 3.7 shows the transverse void fraction distribution averaged in the depth direction (10 mm) for run 1 to run 4. The red vertical dash lines at the bottom of each plot indicate the locations of the air injection holes. From Fig. 3.7 (a) which is taken at $z/D_h = 8.8$, runs 2-4 show five distinct void fraction peaks in the profile. The middle three peaks are located near $x = 9, 15$ and 21 mm which coincide with the air injection holes. The void peaks near the left and right walls are slightly away from the injection hole location, which might be caused by the strong lift force in that region. For run 1 at $j_f = 0.5$ m/s, the effect of injection holes is less obvious compared to other runs, which may be explained by the longer developing time for bubbles traveling from the injection hole to the measurement location. Fig. 3.7 (b) shows the void fraction profile at $z/D_h = 136$. The peaks disappear almost completely and void fraction is rather uniform except the near wall region. As the superficial liquid velocity increases from 0.50 to 1.00 m/s, the wall peak remains at a similar level, but shifted 1 mm towards the wall due to the increased shear gradient. With j_f further

increasing to 2.12 m/s in run 4, the near wall void fraction becomes smaller than the center region though a local peak still exists.

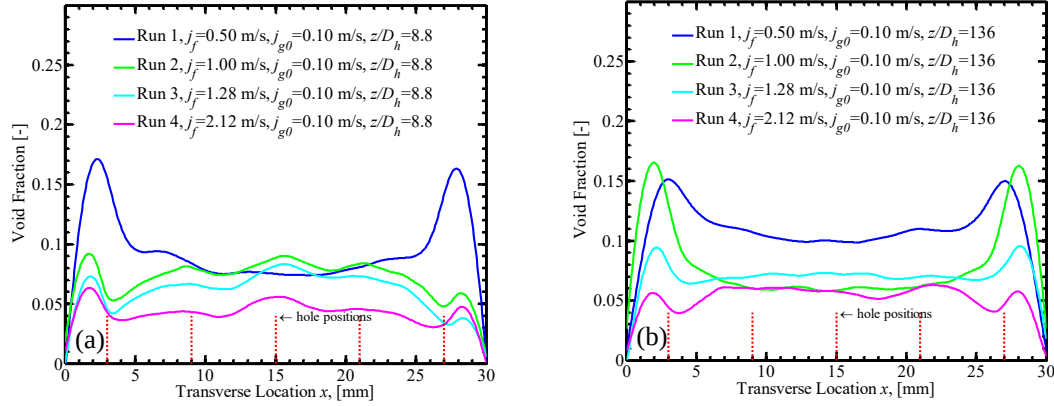


Fig. 3.7 Void fraction distribution of runs 1-4 at (a) $z/D_h = 8.8$ and (b) $z/D_h = 136$.

Fig. 3.8 shows the distributions of the void fraction, interfacial area concentration, bubble velocity, superficial gas velocity, Sauter mean diameter and bubble number density at three measurement ports for run 2. Fig. 3.8 (a) shows that the void fraction profiles at $z/D_h = 72.4$ and 136 are very similar, which indicates the flow has been well developed at port 2. The void fraction peak near the wall is about 0.17, nearly three times higher than that in the center region. The interfacial area concentration shows a similar trend as seen in Fig. 3.8 (b). However, the Sauter mean diameter plotted in Fig. 3.8 (e) shows a continuous increase from port 1 to port 3, which might be caused by the continuously decreasing pressure and gas density. The bubble number density decreases from port 2 to port 3 as shown in Fig. 3.8 (f). This means that the bubble coalescence is more dominant process than the breakup for this run. These two counteracting mechanisms, namely, coalescence and expansion, resulting in a negligible change in the interfacial area concentration between port 2 and port 3.

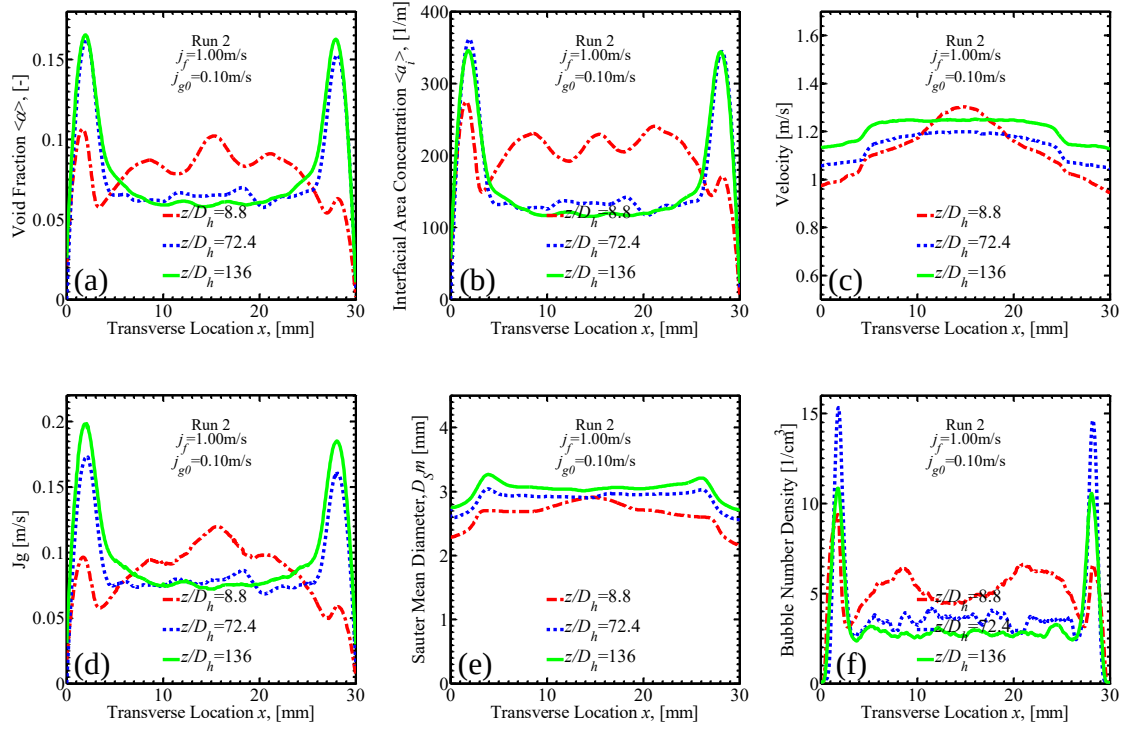


Fig. 3.8 Axial development of bubbly flow parameters in run 2.

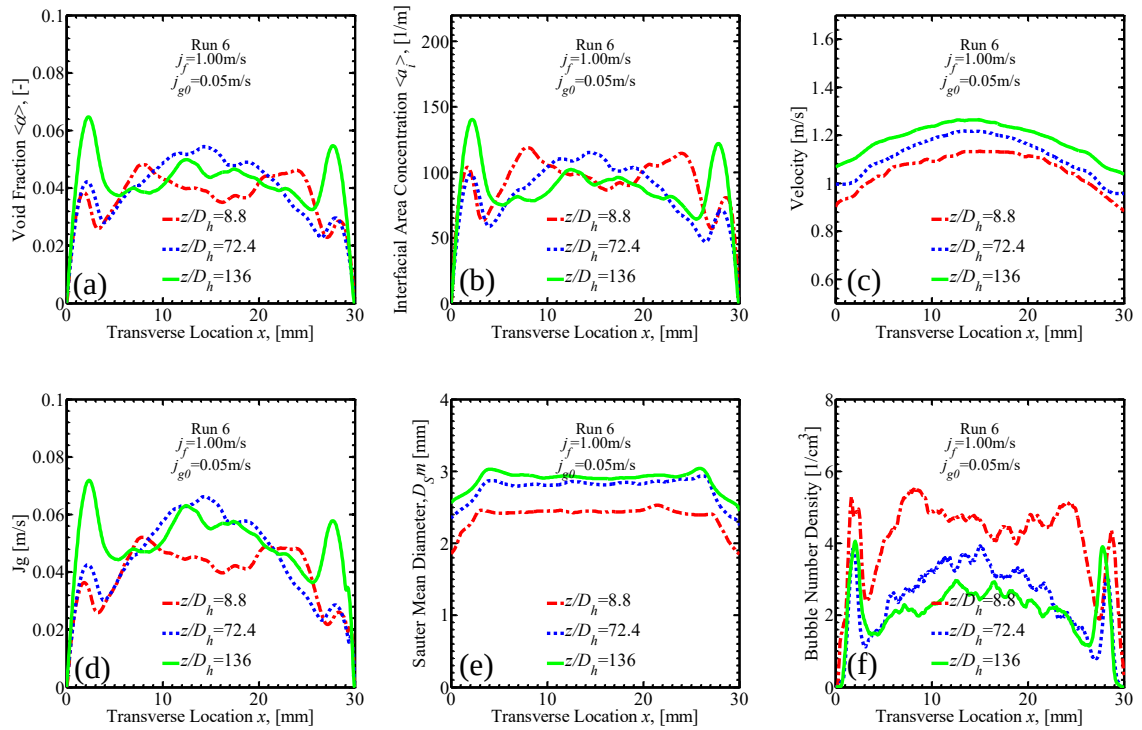


Fig. 3.9 Axial development of bubbly flow parameters in run 6.

For run 6 shown in Fig. 3.9, the wall peak of the interfacial area concentration increases by 40 m^{-1} from the second port to the third. The Sauter mean diameter in Fig. 3.9 (e) shares the same increasing trend with Fig. 3.8 (e). The bubble number density near the left wall in Fig. 3.9 (f) does not change considerably and the right peak shows a slight increase of 0.8 cm^{-3} . Since the void fraction and bubble number density are less than those in run 2, the bubble coalescence should be less frequent. Expansion and lift force effect might be the dominant mechanisms in this case which lead to a significant increase of interfacial area concentration at the near wall region.

The bubble velocities in both runs show a continuous increasing trend from port 1 to port 3. The velocity profiles are relatively flat compared with single-phase laminar or turbulent profiles. It is also noted that the velocities take finite values at the left and right wall boundaries, which is quite different from the no-slip wall boundary condition typically found in single-phase flows. This difference is consistent with the experimental observations, namely, even the bubbles at the wall could slide along the wall with a non-zero velocity. It should be noticed that the bubble semi-axis which is perpendicular to the camera axis is assumed to be equal to the short semi-axis of the fitted ellipse on the bubble reconstructed outline. This assumption enables the algorithm to estimate the bubbly flow void fraction and interfacial area concentration. With no extra information provided, this assumption can be an important error source in estimating the void fraction and interfacial area concentration with a single 2D image only in studying the bubbly flow. The uncertainty of one camera system in measuring the bubbly flow parameters is further studied in Chapter 4.

3.3.2 Development Along Axial Direction

To study the one-dimensional development of bubbly flows, the cross-sectional area-averaged data are obtained for all eight runs at three ports as shown in Fig. 3.10. The void fraction of all runs shows a monotonic increasing trend. Considering that the velocity also has an increasing trend, the volumetric flow rate increases along the test channel, which is consistent with the pressure decreasing trend. For runs 5-8 with a fixed $j_{g0} = 0.05 \text{ m/s}$, the bubble number density in Fig. 3.10 (e) becomes smaller at a higher elevation. For runs 1-4, the gas velocity is fixed at $j_{g0} = 0.10 \text{ m/s}$. The bubble number density in Fig. 3.10 (b) shows a more complicated behavior. Bubble number density drops from port 2 to port 3 in runs 1, 2 and 3. For run 4, the number density

increases first from port 1 to 2 and then decreases from port 2 to 3. Both the void fraction and number density have a direct influence on the interfacial area concentration change. As shown in Fig. 3.10 (c) and Fig. 3.10 (f), the interfacial area concentration shows quite different trends from port 1 to port 3, among different runs.

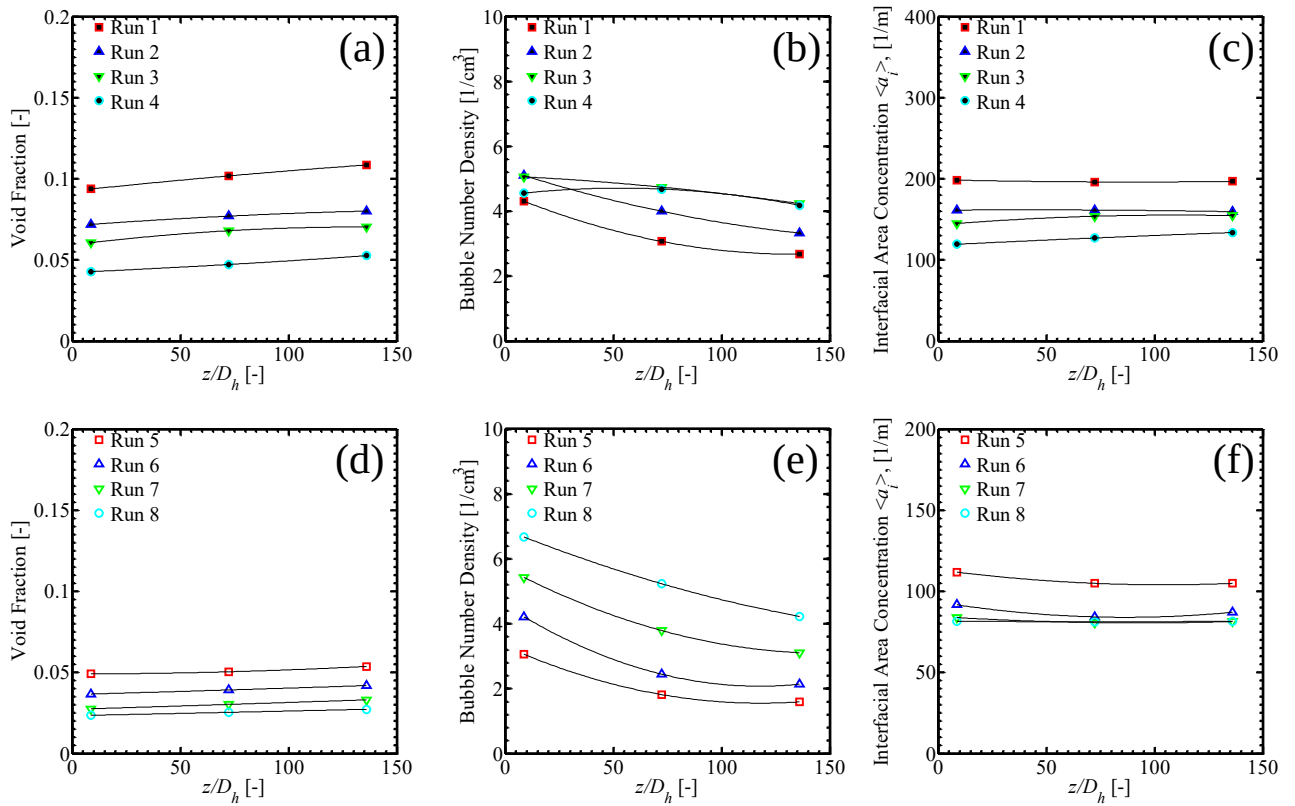


Fig. 3.10 Axial development of area-averaged parameters for runs 1-8.

3.4 IATE Benchmark

For adiabatic air-water two-phase flows, the main source terms in the interfacial area transport equation come from the bubble expansion and bubble interaction mechanisms. For one-dimensional IATE benchmarking, the expansion effect can be obtained directly from the pressure changes. According to Sun *et al.* (2004), there are three typical bubble interaction mechanisms in bubbly flows: (1) random collision (RC), (2) wake entrainment (WE), and (3) turbulent impact (TI). The random collision and wake entrainment are sink terms, whereas the turbulent impact acts as a source term. The one-dimensional area-averaged IATE for bubbly flow condition can be written as [54]:

$$\frac{d}{dz}(\langle a_i \rangle \langle v_{gz} \rangle) = \left(\frac{2}{3} - C(D_c^*)^2 \right) \frac{\langle a_i \rangle}{\langle \alpha \rangle} \frac{d}{dz}(\langle \alpha \rangle \langle v_{gz} \rangle) + \sum_j \langle \phi_j \rangle, \quad (3.1)$$

where v_{gz} is the bubble velocity in the axial direction (z); C is the intergroup transfer coefficient; D_c^* is the ratio of critical diameter to Sauter mean diameter and the ϕ_j represent the j^{th} bubble interaction mechanism. In the current IATE benchmarking study, the source term models and model coefficients proposed by Sun *et al.*[54] are used.

While solving Eq. (3.1), the bubble velocity and void fraction data obtained from the image processing technique are used as known parameters, which eliminates the need for solving the continuity and momentum equations. The interfacial area concentration measured at the first port $z/D_h = 8.8$ are used as the inlet boundary condition. The interfacial area concentration predicted by the IATE model at $z/D_h = 72.4$ and 136 are compared with the measured data as shown in Fig. 3.11. As can be seen, the IATE model performs very well for runs 3-6, with most data being predicted within an error range of $\pm 10\%$. Several major sources contributed to the change of the interfacial area concentration can be found in the right column in the figure. The expansion acts as the major source term for all four conditions. The wake entrainment is the dominant bubble interaction mechanism which acts as a sink for interfacial area transport. Whereas the random collision and turbulent impact show negligible effect since the void fraction is low and the Weber number is smaller than the critical Weber number (6.5). The velocity always increases along the test channel so that it shows a negative effect on the interfacial area concentration change. The combined effect of expansion, velocity and random collision results in an overall increasing trend in runs 3 and 4, but nearly random fluctuations for runs 5 and 6.

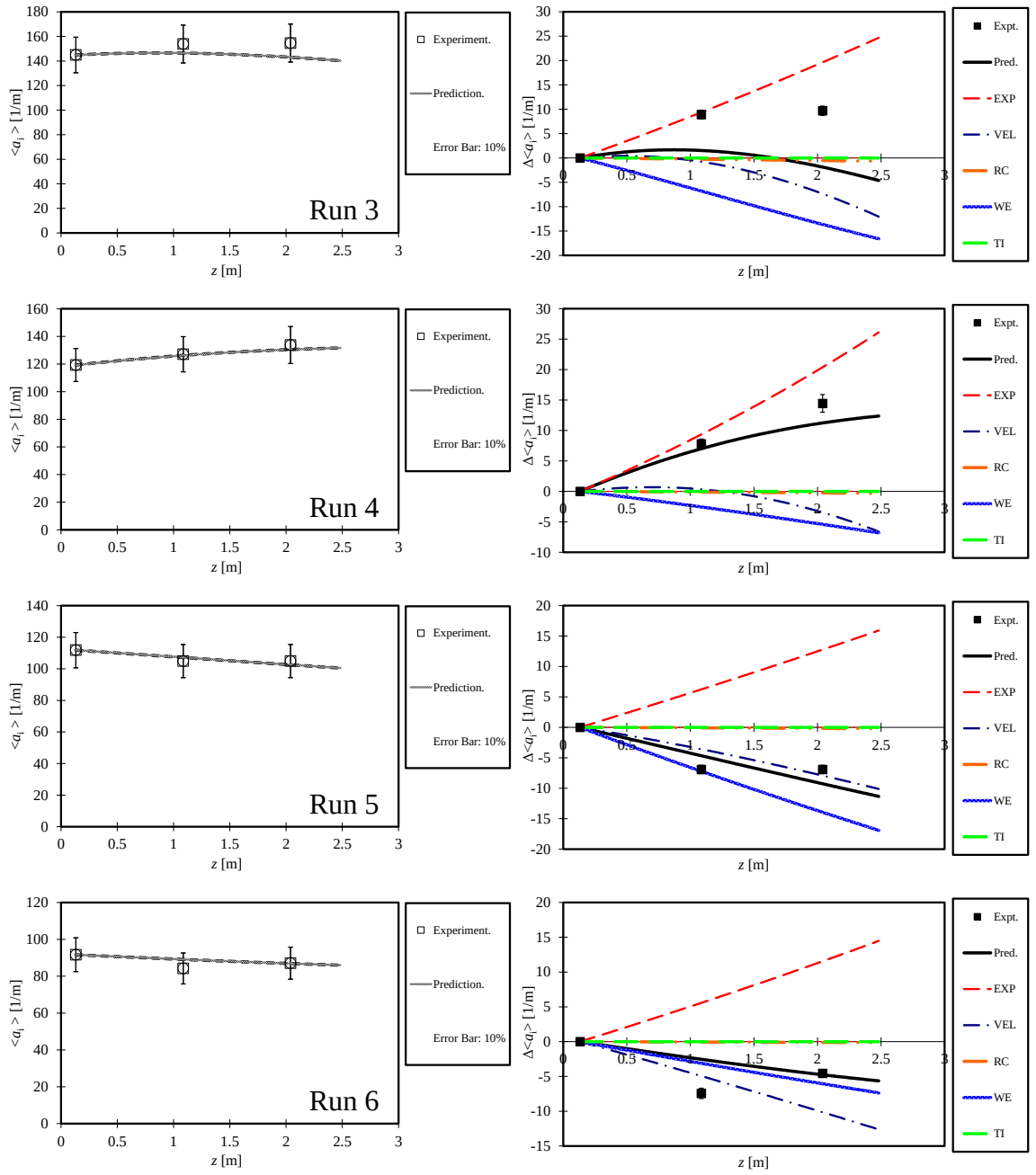


Fig. 3.11 Left: comparison of the interfacial area concentration prediction with experimental data for runs 3-6; right: contribution of various source and sink terms.

3.5 Number Density Transport Equation Benchmark

The image processing technique can accurately measure the bubble number density, which cannot be obtained by other methods such as the conductivity probe, or wire mesh sensor (due to size limit). The IATE is derived based on the Boltzmann transport equation of the bubble number density function. Therefore, it is important to validate the number density transport equation and the related bubble interaction mechanisms with the current data. This study will provide a more fundamental understanding of the bubble interactions as it can separate other effects such as the bubble shape modeling and volume expansion from the equation. The number density transport equation for bubbly flow is given as[54]:

$$\frac{\partial n_1}{\partial t} + \nabla \cdot (n_1 \vec{v}_{pm1}) = R_{RC} + R_{WE} + R_{TI}, \quad (3.2)$$

where n_1 is the bubble number density and $\vec{v}_{pm1}$ is the number-density-weighted bubble velocity; R_{RC} and R_{WE} are bubble coalescence rate due to random collision and wake entrainment, respectively; R_{TI} is the bubble break up rate due to turbulent impact. Since the current tests are performed in adiabatic air-water condition, the terms due to nucleation and condensation are not considered here.

Similar to IATE, the number density transport equation is solved using the bubble velocity and void fraction obtained from image processing scheme as known parameters. The number density in the first port $z/D_h = 8.8$ is used as inlet boundary condition. Fig. 3.12 shows the comparison results of the number density at the second and third port for runs 3-6. In these runs, the model shows that the wake entrainment and the velocity change are the two major factors which cause the decrease of the bubble number density. The influence of random collision and turbulent impact are negligible, similar to the interfacial area transfer. For runs 3 and 4 with $j_{g0} = 0.1$ m/s, the figures show that the model performs quite well with a relative error of about $\pm 10\%$. For runs 5 and 6 with $j_{g0} = 0.05$ m/s, the model correctly predicts the decreasing trend but underestimates the bubble coalescence rate. The number density acquired from the experiment is significantly lower than the prediction. This shows some inconsistency compared to the IATE results for run 5 and 6 as shown in Fig. 3.12, in which experimental data are well predicted by the IATE. One main reason may be that the coefficients determined for the sink and source terms in IATE have to account for both the bubble number density transport and the bubble shape

approximation to obtain the optimized values for interfacial area transport. However, these coefficients may not be the optimal values for the number density transport equation alone.

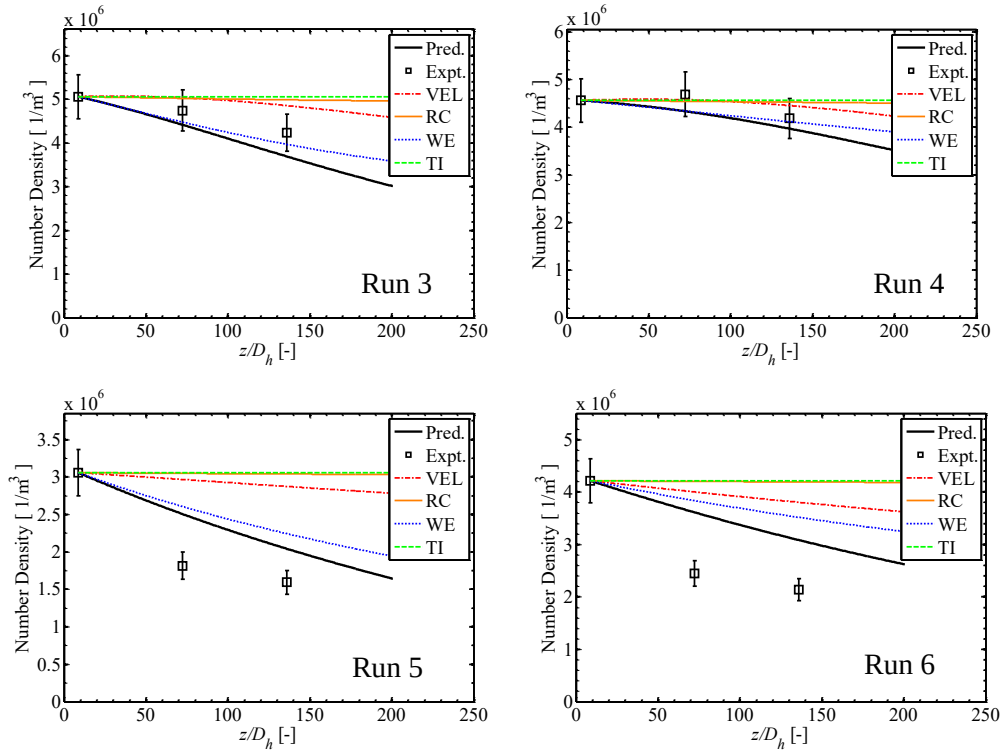


Fig. 3.12 Comparison of the number density prediction with the experiment data for runs 3 - 6.

3.6 Summary

This Chapter studied the air-water bubbly flows in a 30 mm × 10 mm rectangular channel. The test conditions cover two superficial gas velocities, 0.05 and 0.10 m/s with different superficial liquid velocities ranging from 0.50 to 2.12 m/s. Three high-speed cameras located at $z/D_h = 8.8$, 72.4 and 136 were synchronized to capture the development of bubbly flow in both transverse and axial directions. The proposed 2D image processing algorithm was used to extract the information of individual bubbles, as well as the temporally and spatially averaged parameters. The image processing technique can effectively identify and reconstruct overlapping bubbles for local void fraction up to 17%. The lift force effect was observed in several test runs, which drives bubbles to the near wall region. The interfacial area concentration shows a complicated behavior since several sources and sink mechanisms are competing with each other. The predictions made by the one-dimensional IATE model compare reasonably well with the data extracted by the image processing scheme. The number density transport equation shows a discrepancy with the

experimental data in some cases. This may be a result of the unoptimized empirical coefficients in the bubble interaction mechanisms and should be carefully treated in the future studies.

4 3D Bubble Reconstruction Algorithm with Multiple Cameras

4.1 Introduction

To accurately measure the 3D shape of bubbles and to evaluate the accuracy of 1- and 2-camera systems, an imaging system employing four synchronized high speed cameras is developed for 3D bubble reconstruction. The existing 3D object reconstruction algorithms include digital holography [55,56], shape from silhouette [57,58], shape-from-texture [59], etc. Considering the transparent surface and deformation of the bubble in liquids, no well-marked textures can be extracted from the bubble surface for applying the shape-from-texture technique. With the ambient LED light setup in this experiment, a shape from silhouette based space carving method is proposed to process the obtained high speed images for 3D bubble reconstruction. This method can combine the bubble projections from different view angles to generate a visual hull, which represents the maximum possible space containing the bubble. A smooth bubble shape can then be fitted in the visual hull. Compared to the 1- and 2-camera systems, the developed system can measure bubble shape with higher accuracy and less uncertainty. The bubble parameters: volume, surface area, rotation angle and aspect ratio are also made available with the reconstructed bubble. This method is flexible with the camera position and numbers, which can be adopted to measuring bubbly flow in different experiment setups. It also provides a baseline data for the evaluation of the performance of the 1- and 2-camera systems.

In this chapter, the experimental setup and the 3D imaging system are first described. Existing bubble reconstruction techniques are then reviewed based on the number of high speed camera used for reconstruction. The proposed space carving algorithm is followed after these methods. A 3D synthetic bubble model is used to verify the accuracy of the space carving method and to analyze the uncertainty of the aforementioned methods for 3D bubble shape measurement. After algorithm verification, different reconstruction techniques are used to measure the bubbles injected into the stagnant water in a rectangular channel. The accuracy and uncertainty of these methods are obtained by comparing the bubble volume measurement within the known injection volume. The wall influence on bubble rotation is studied by visualizing the bubble trajectory in a sequence of frames. Bubble rotation angle and aspect ratio measurement using the proposed technique are provided at the end of this chapter.

4.2 Experimental Setup and Image Pre-processing

4.2.1 3D Imaging System

High speed images are taken on gas bubbles in the 3 m tall test channel with a $3\text{ cm} \times 1\text{ cm}$ rectangular cross-section. The details of the test facility can be found in Section 2.2. In this task, tests are carried out in stagnant water condition with the water column height of $z/D_h = 131.7$. A syringe with an accuracy of $\pm 10\text{ mm}^3$ is used for bubble injection. The gas bubble is injected into the water column through a stainless steel tube placed at the center of the inlet. The stainless steel tube has an inner diameter of $ID = 1.20\text{ mm}$. In each run, the total injected gas volume is around 900 mm^3 . The test is repeated 10 times, which results in 331 bubbles in this study.

The configuration of the four high speed camera imaging system is illustrated in Fig. 4.1. As shown in the figure, the system consists of four high speed cameras (Photron FASTCAM SA4) placed at the same dimensionless height of $z/D_h = 25$ along the test channel. All four high speed cameras are synchronized at a frame rate of 250 Hz for image recording. The resulted 8-bit grayscale image has a maximum resolution of $1024\text{ pixels} \times 1024\text{ pixels}$. Camera 2 and camera 4 are perpendicular to the front (3 cm wide) and side (1 cm wide) walls of the test channel, respectively. Camera 1 is placed to the right of camera 2 with an angle of 39° . Camera 3 is placed to the left of camera 1 with an angle of 50° . These angles are measured after the cameras have been installed at their optimal locations under the condition that the physical space is limited by the test section supporting structures.

The extrinsic and intrinsic parameters of four cameras are calibrated with a chessboard target and Matlab (The Mathworks, Inc., R2017a) image processing toolbox. The camera orientation and the magnification ratio with a given distance to the camera can be acquired from the camera intrinsic parameters. The relative location and orientation of four cameras can be determined from the extrinsic parameters. The spatial resolution of the recorded images is around 30 pixels per mm and it varies depending on the bubble location and the recording camera. Two LED panels are placed on the opposite side of the front and side cameras to provide backlit illumination for the imaging system. To facilitate the following discussion, the origin of the world coordinate system (x - y - z) is set at the bottom left corner of the test channel inlet plane, with the positive z -axis pointing upward. The x and y axes are aligned parallel to 30 mm and 10 mm wall side, respectively. The i^{th} camera coordinate is denoted as $(x_{ci}-y_{ci}-z_{ci})$ in the following discussion.

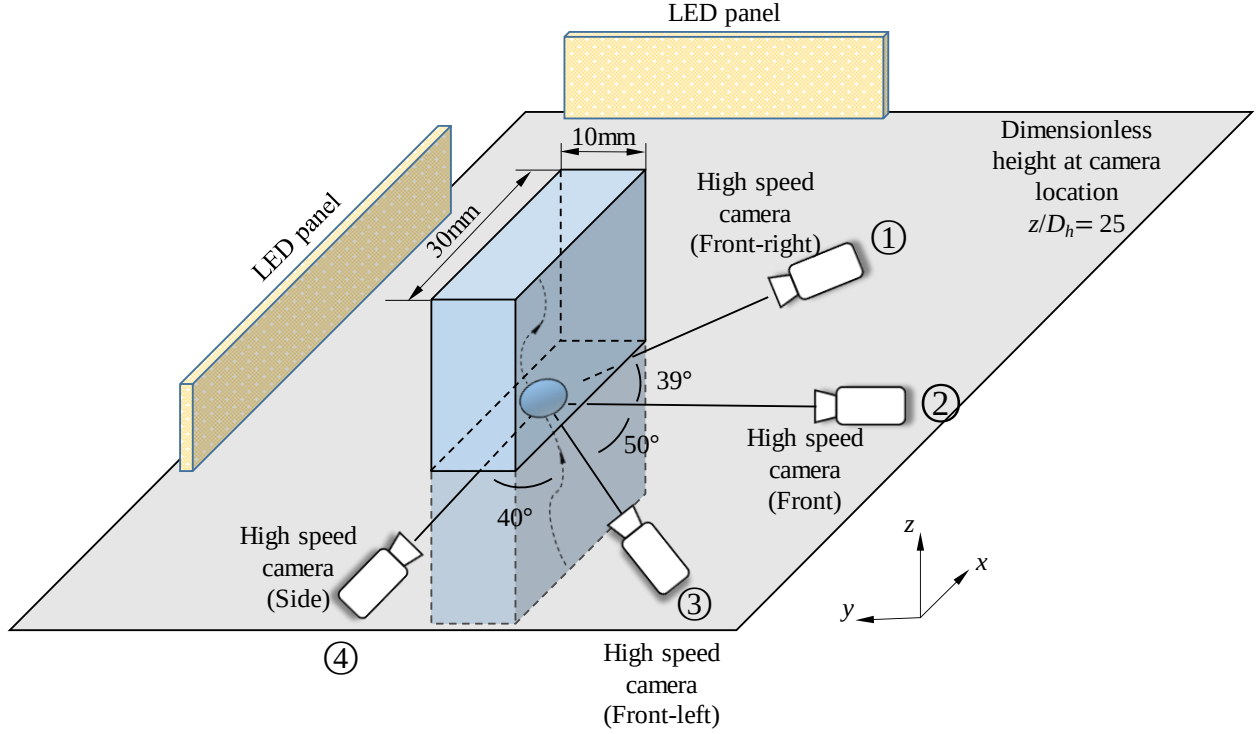


Fig. 4.1 Configuration of the imaging system with four high speed cameras at the height of $z/D_h=25$.

4.2.2 Distortion Correction

The calibration chessboard is placed on the outside of the test channel due to limited access to the inside. The distortion due to light refraction at the water-acrylic-interface and acrylic-air-interface are corrected by ray tracing method. A schematic of the ray path is shown in Fig. 4.2 (a) for the front high speed camera. The actual bubble size is denoted as d_{org} and the solid red line shows the forward ray from the bubble to the camera after refraction. From the backward projection, the bubble size will be d_{pro} in the image as indicated by the red dashed lines. With the known refractive indices of water and acrylic, the ray path can be reconstructed to calculate the magnification ratio of bubbles $m = d_{pro}/d_{org}$. Fig. 4.2 (b) shows the variation of the magnification ratio m with the bubble location inside the 10 mm thick channel for the front camera. As can be seen in the figure, the magnification ratio increases linearly with the bubble distance to the front wall. The averaged magnification ratio of the front camera is around 1.043. For the rest three

cameras, the magnification ratio is corrected by matching the height of the bubble with the image taken by the front camera. This should give an accurate result since the bubble height remains the same when images are taken from different angles at the same elevation.

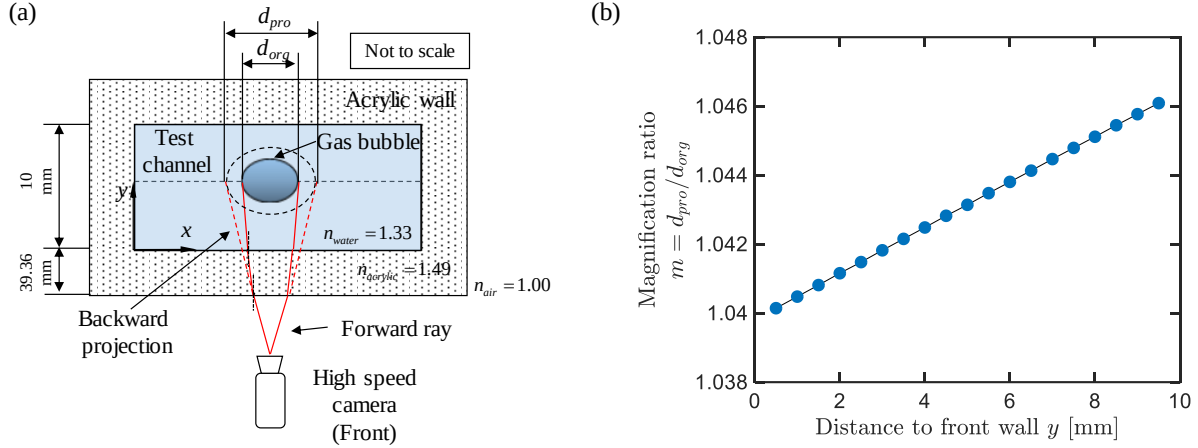


Fig. 4.2 (a) Illustration of bubble size distortion due to light refraction at the water-acrylic and air-water interfaces, (b) variation of the magnification ratio m with the wall distance for the front camera.

4.2.3 Camera Coordinate and Bubble Shape Model

The mapping from the world coordinate which is fixed on the test channel to the image plane is illustrated by Fig. 4.3. In this transformation, the first step is to convert an object location (x, y, z) in the world coordinate to (x_{ci}, y_{ci}, z_{ci}) in the i^{th} camera coordinate with known extrinsic parameters $[\mathbf{R} \ \mathbf{t}]$, where $\mathbf{R}$ stands for the rotation matrix and $\mathbf{t}$ is the translation matrix. With the calibrated intrinsic matrix $\mathbf{K}$, the corresponding pixel location (u, v) of the object can be obtained from the camera coordinate. More details of camera calibration and parameter descriptions can be found in Zhang's work [60]. The overall transformation from the world coordinate to imaging plane can be expressed as:

$$s \begin{pmatrix} u \\ v \\ 1 \end{pmatrix} = \mathbf{K}[\mathbf{R} \ \mathbf{t}] \begin{pmatrix} x \\ y \\ z \end{pmatrix}, \quad (4.1)$$

where s is a scaling factor to normalize the result vector. The above equation can be simplified as:

$$\mathbf{u} = \begin{pmatrix} u \\ v \end{pmatrix} = T(\mathbf{x}), \quad (4.2)$$

where T represents the transformation matrix from Eq. (4.1).

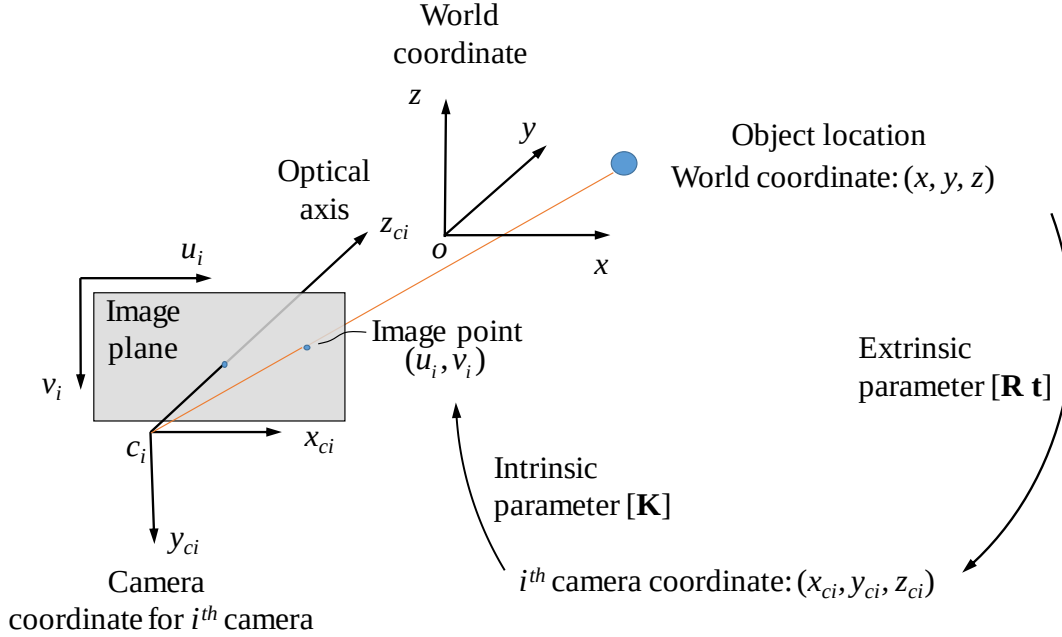


Fig. 4.3 Mapping 3D points from world coordinate to the 2D pixel location on camera image plane using pinhole camera model.

In a world coordinate, an arbitrary bubble B can be represented as a set of points $\mathcal{V}$ that occupied by the bubble:

$$\mathcal{V} = \left\{ \mathbf{x} \in \mathbb{R}^3 \mid \mathbf{x} \in B \right\}, \quad (4.3)$$

and the bubble outline enclosed area on the camera image plane is written as:

$$\mathcal{M} = \left\{ \mathbf{u} \in \mathbb{R}^2 \mid \mathbf{u} = T(\mathcal{V}) \right\}. \quad (4.4)$$

The surface of the bubble B is written as:

$$\partial\mathcal{V} = \left\{ F(\mathbf{x}) = 0 \mid \mathbf{x} \in \mathcal{V} \right\}, \quad (4.5)$$

where F is the level set function describing the bubble surface. If a bubble has an ellipsoidal shape, the surface can be written in a quadratic form as:

$$F(x, y, z) = a_{11}x^2 + a_{22}y^2 + a_{33}z^2 + 2a_{12}xy + 2a_{23}yz + 2a_{13}xz + 2b_1x + 2b_2y + 2b_3z + d = 0. \quad (4.6)$$

Rearrange it, the matrix form of an ellipsoidal bubble is:

$$\mathbf{x}^T \mathbf{A} \mathbf{x} + \mathbf{J}^T \mathbf{x} + d = 0, \quad (4.7)$$

where $\mathbf{A}, \mathbf{J}, \mathbf{x}$ are given as:

$$\mathbf{A} = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix}, \mathbf{J} = \begin{bmatrix} 2b_1 \\ 2b_2 \\ 2b_3 \end{bmatrix}, \mathbf{x} = \begin{bmatrix} x \\ y \\ z \end{bmatrix}. \quad (4.8)$$

4.2.4 2D Image Processing

Sample bubble images recorded by the imaging system are shown in Fig. 4.4. From left to right, the four images are captured by the front-left, front, front-right and side cameras for the same bubble. The red line represents the bubble outline obtained by the 2D image processing algorithm. In this experiment, the bubbles are injected from a single tube, and the flow rate is relatively small. Therefore, the bubble overlapping issue, which could occur at higher void fraction conditions, is not encountered here. This greatly simplifies the processing of 2D images and ensures the accuracy of the extracted bubble outlines from different cameras. The bubble trajectories and shape oscillations within each camera can be also tracked using the algorithm by processing a sequence of consecutive frames. As mentioned in section 4.2.1, the camera position and orientation is calibrated before performing the test. Thus, the corresponding bubble in each camera can be matched accordingly with this information.

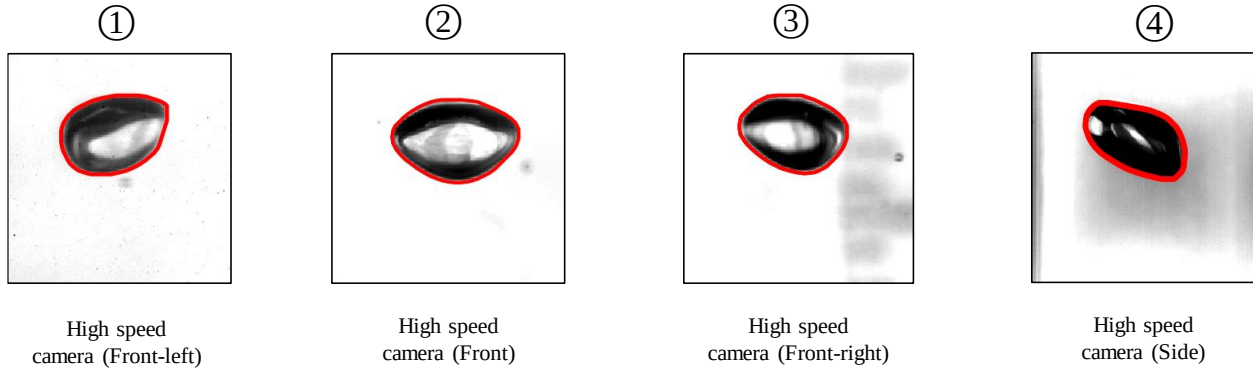


Fig. 4.4 Sample images of a gas bubble recorded by the imaging system. The red line represents the bubble outline extracted by the image processing algorithm.

4.3 Bubble Reconstruction Algorithm

The existing 3D bubble reconstruction algorithms are summarized briefly in this section. High speed images recorded at a specific location (or a view angle) is denoted as one view. In some experiments, mirrors are used to direct different views to the same camera. In these cases, one camera can record two or more views. In the following discussion, each camera is assumed to record only one view, which is the case in the current study. The general strategy for bubble reconstruction is summarized in Fig. 4.5. Depending on the available views in an experiment, different techniques can be used to fulfill the reconstruction task. As summarized in the figure, one can use bounding box, ellipse fitting and slicing methods for one view bubble reconstruction. With only one view, assumptions must be made for the third dimension of the bubble to calculate volume and surface area. With two views, more information can be obtained from the images and these methods can be used with fewer assumptions. Also, all three coordinates of the bubble location and three components of the velocity vector can be determined in this case. The implementation of the bounding box and slicing method is straightforward. For the ellipse fitting method, bubble is approximated by an ellipsoid in 3D space. This is obtained by first fitting 2D images with ellipse functions, and then reconstructing the ellipsoid function from two ellipse functions corresponding to two views. With three or more views, an over-determined system will be formed for these methods. Thus the information from the additional views may not be fully utilized. The proposed space carving method can be implemented when two or more views are

available. The method can achieve higher accuracy with the increase of the number of views. The details of these reconstruction methods are discussed below.

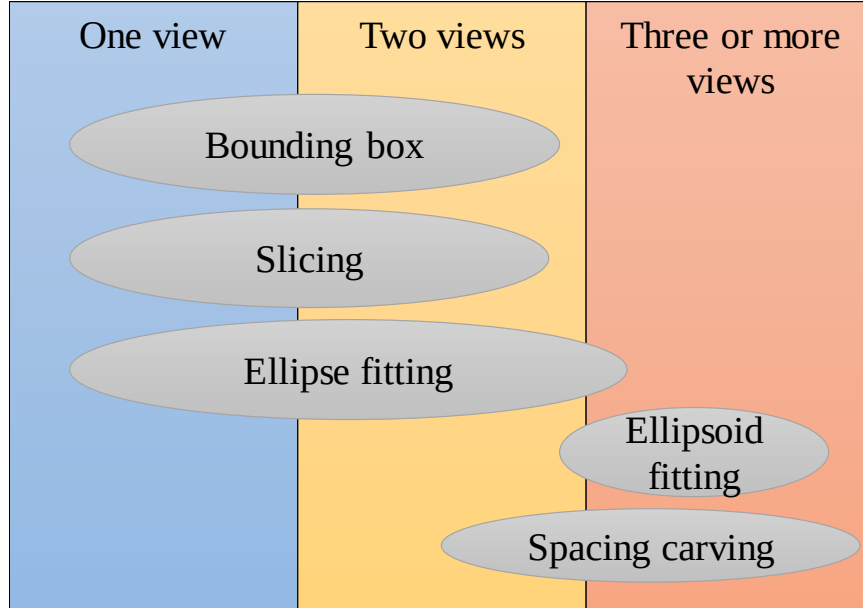


Fig. 4.5 Bubble reconstruction algorithm classification based on camera views.

4.3.1 Bounding Box Method

The bounding box method is a widely used method for estimating bubble volume, bubble diameter, and aspect ratio, etc. when only one camera view is available [22,33,61]. This method finds the minimum rectangular box that contains the bubble projection inside. If the bubble projection minor axis aligns with the flow direction, the width d_w and the height d_H of the bounding box can be used to represent the major and minor axis of the bubble projection outline. By assuming the bubble has an oblate shape and the third axis along the projecting direction is equal to d_w , the bubble volume V_B is calculated as [33]:

$$V_B = \frac{\pi}{6} d_w^2 d_H. \quad (4.9)$$

The bubble volume can also be expressed in terms of the volume equivalent diameter d_v as:

$$V_B = \frac{\pi}{6} d_v^3. \quad (4.10)$$

Combining Eq. (4.9) and Eq. (4.10), the relationship between d_w , d_H and d_v can be derived as:

$$d_v = \sqrt[3]{d_w^2 d_H} . \quad (4.11)$$

The bubble aspect ratio is calculated as [34]:

$$E = \frac{d_H}{d_w} . \quad (4.12)$$

The horizontal width of the bubble d_w is also used as a characteristic length of the bubble in some modeling works. For example, in the derivation of the lift force model, the modified Eötvös number is defined based on the horizontal width rather than the volume equivalent diameter [61].

4.3.2 Slicing Method

In slicing method, the shape of the projection is utilized in bubble reconstruction, which provides more information when calculating surface area and volume compared to the bounding box method. This method may have better accuracy if the bubble is not a perfect sphere or ellipsoid due to surface deformation and bubble rotation. Slicing method is suitable for either one or two cameras [38,48,62,63]. The schematic of the implementation of slicing method is shown in Fig. 4.6. In the figure, the bubble is assumed to move along the z direction.

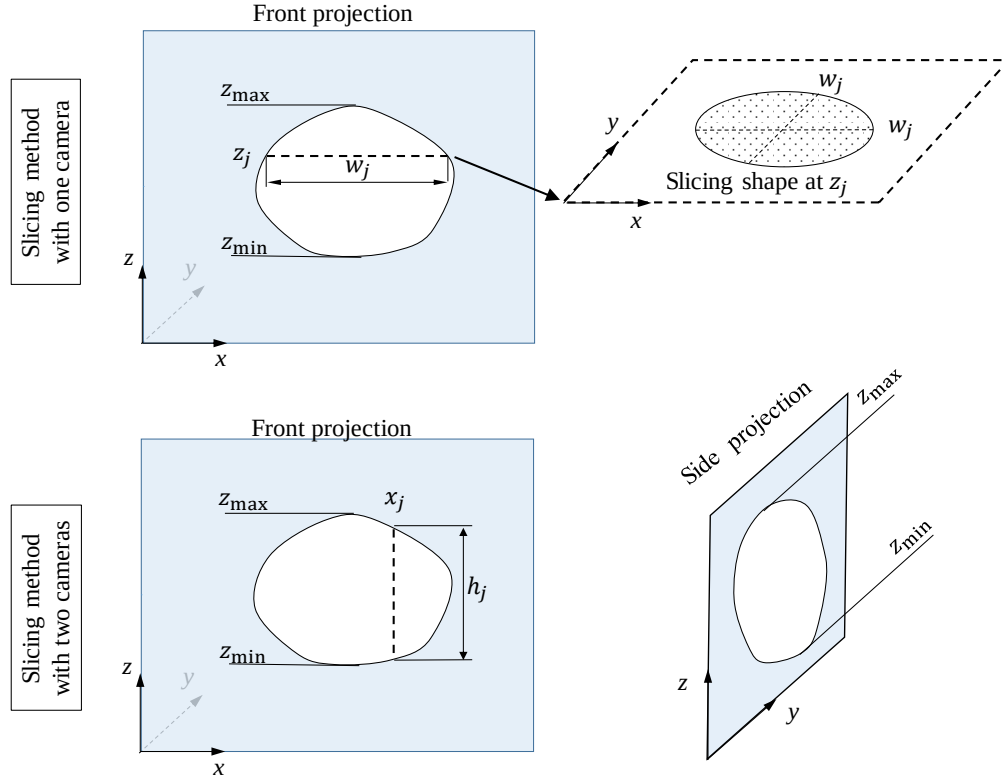


Fig. 4.6 Bubble shape reconstruction using slicing method with one (top) or two (bottom) cameras.

If the bubble outline is acquired from one view only, the bubble surface is reconstructed in the following way. First, the bubble projection in the x - z plane is divided into a sequence of slices from $z_{\min}$ to $z_{\max}$. For a slice at the height of z_j , the width w_j in the x direction can be obtained from the projection directly. Since the information in the y direction is unknown, the cross-sectional shape at height z_j is assumed to be a circle with a diameter of w_j . By stacking up the slices from bottom to top, a 3D bubble can be reconstructed. When the 3D bubble is projected back to the image plane, the same outline will be obtained as that from the recorded image.

When two views of the same bubble are available, more details can be uncovered during the reconstruction. In this work, the front and side cameras are used for the two-view slicing method. In this case, both the projection in the x - z plane and that in the y - z plane will be available. The bubble in the x - z plane will be sliced vertical from right to left. At each slice location x_j , the bubble is assumed to have a similar shape to that acquired from the projection on the y - z plane. However, the original side projection has to be downscaled to match the height between the front and side views. The scaling factor is given by the ratio of the height h_j at x_j and the maximum height d_H of

the bubble. A 3D bubble can be reconstructed by piling up the slices from left to right. When the 3D bubble is projected back to the image plane, the same outline will be obtained for both the front and side cameras.

4.3.3 Ellipse Fitting Method

Ellipse or ellipsoid are often used to approximate the shape of bubbles. Due to surface instability and fluctuation of surrounding liquid, the bubble shape may not be perfectly smooth even in high Morton number and low turbulent intensity conditions. Using an ellipse fitting method can remove the noises from the projection and extract important bubble information such as semi-axes, rotation angle, and aspect ratio, *etc.* Ellipse fitting of the bubble projection view is essentially an optimization problem and has been widely studied in the literature [64,65].

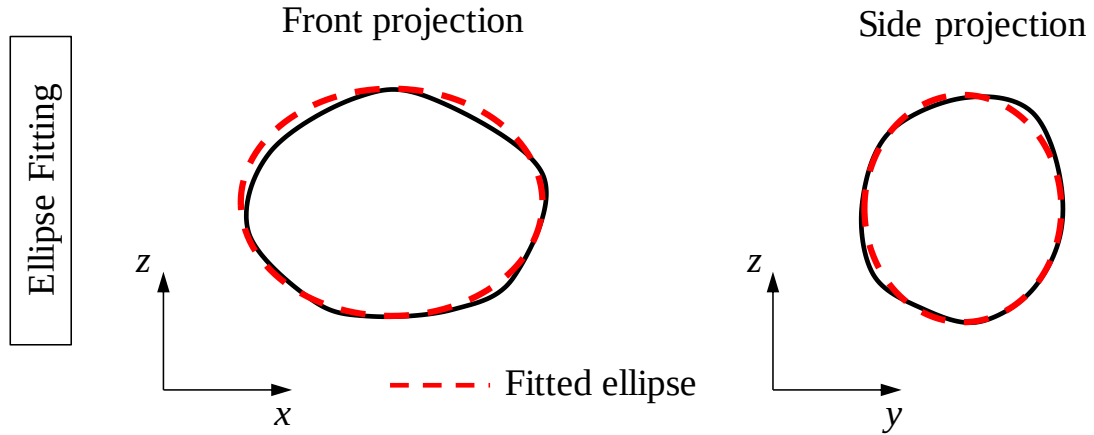


Fig. 4.7 Bubble shape reconstruction using ellipse fitting method with two cameras.

With two projection views, the ellipse fitting method can be carried out in two steps. As shown in Fig. 4.7, 2D ellipse fitting method is first used to fit ellipses for both the front and side views. The obtained ellipse models are denoted as:

$$\begin{aligned} \text{Front view: } C_1x^2 + C_2z^2 + C_3xz &= 1, \\ \text{Side view: } C_4y^2 + C_5z^2 + C_6yz &= 1. \end{aligned} \tag{4.13}$$

Considering an ellipsoid model for the 3D bubble surface:

$$a_{11}x^2 + a_{22}y^2 + a_{33}z^3 + 2a_{12}xy + 2a_{23}yz + 2a_{13}xz + 2b_1x + 2b_2y + 2b_3z + d = 0, \quad (4.14)$$

these parameters can be related as:

$$\begin{aligned} a_{22} &= a_{11} \frac{4C_4C_5 - C_6^2}{4C_1C_2 - C_3^2}, & a_{12} &= \pm \sqrt{a_{22}a_{11} - C_4a_{11}}, \\ a_{23} &= \frac{C_3a_{12} + C_6a_{11}}{2C_1}, & a_{13} &= \frac{C_6a_{12}a_{11} + C_3a_{11}a_{22}}{2C_1a_{22}}, \\ a_{33} &= \frac{C_5a_{11} + a_{13}^2}{a_{11}}. \end{aligned} \quad (4.15)$$

By assuming the bubble has a minimum rotation angle along the z direction, a_{11} can be chosen as a free parameter for searching the optimized coefficients of a_{12} to a_{33} . Then, the bubble shape can be recovered with the ellipse fitting method.

4.3.4 Space Carving Method

The space carving method generates a visual hull of the bubble based on the projection image from different views. This method is more flexible on the number of views available and does not require cameras to be placed at the same level. With more views available, it is expected that the accuracy would increase accordingly. For bubble shape reconstruction, at least two views of a bubble are required for the implementation of this method. To obtain an accurate shape of a non-regular shape bubble, three or more views are desired.

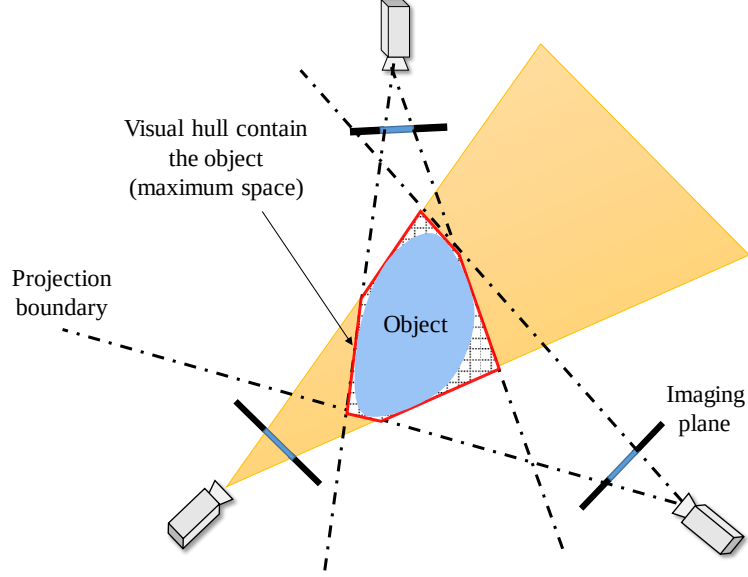


Fig. 4.8 Illustration of space carving method with three cameras.

Fig. 4.8 shows an example of how the space carving method is implemented with three cameras. To implement this method, the location and direction of each camera should be calibrated in advance. Combining the bubble projection and camera position, the bubble image can be projected back into the 3D space. This will define a silhouette cone within which the bubble may exist. The points inside the silhouette cone can be denoted as:

$$\mathcal{U} = \left\{ \mathbf{x} \in \mathbb{R}^3 \mid T(\mathbf{x}) \in \mathcal{M} \right\}. \quad (4.16)$$

In a multiple camera imaging system, each camera will generate a silhouette cone. The union of the 3D point sets can form the point clouds $\mathcal{U}_F$ as:

$$\mathcal{U}_F = \mathcal{U}_1 \cap \mathcal{U}_2 \dots \cap \mathcal{U}_N, \quad (4.17)$$

where N is the number of available cameras. $\mathcal{U}_F$ defines the maximum possible volume of the bubble, or in other words, the actual bubble is a subset of $\mathcal{U}_F$. The surface of $\mathcal{U}_F$ is called visual hull $\partial \mathcal{U}_F$, which is highlighted as a red polygon in Fig. 4.8. In general, a bubble will not fill the entire visual hull due to surface tension force, which prevents the forming of sharp corners. Additional smoothing steps should be used to approximate the bubble surface based on the obtained visual hull.

The implementation details of the current four-camera system are illustrated in Fig. 4.9. The space carving method starts with images obtained from the front and side cameras as shown in

step 1. The number marked on the visual hull represents the camera number which carved the corresponding surface. A coarse visual hull can be obtained from these two cameras. In step 2 and step 3, additional camera images from different view angles are added. As can be seen, the visual hull becomes more and more refined each time when a new camera view is added.

To smoothen the bubble surface, the obtained visual hull is divided into multiple slices along the z direction. These slices have octagon shape with 8 edges carved by four high speed cameras. In general, sharp edges do not exist in actual bubbles due to the surface tension force. In step 5, a spline-fitting is performed to connect all the mid points in each edge to form a smooth outline of the bubble inside the given polygon. Then, the reconstructed outlines in different slices are piled up to form a 3D surface of the bubble as shown after step 6. It should be noted that when the reconstructed 3D bubble is projected back to the image plane, same outline as the recorded image will be obtained for each of the four cameras.

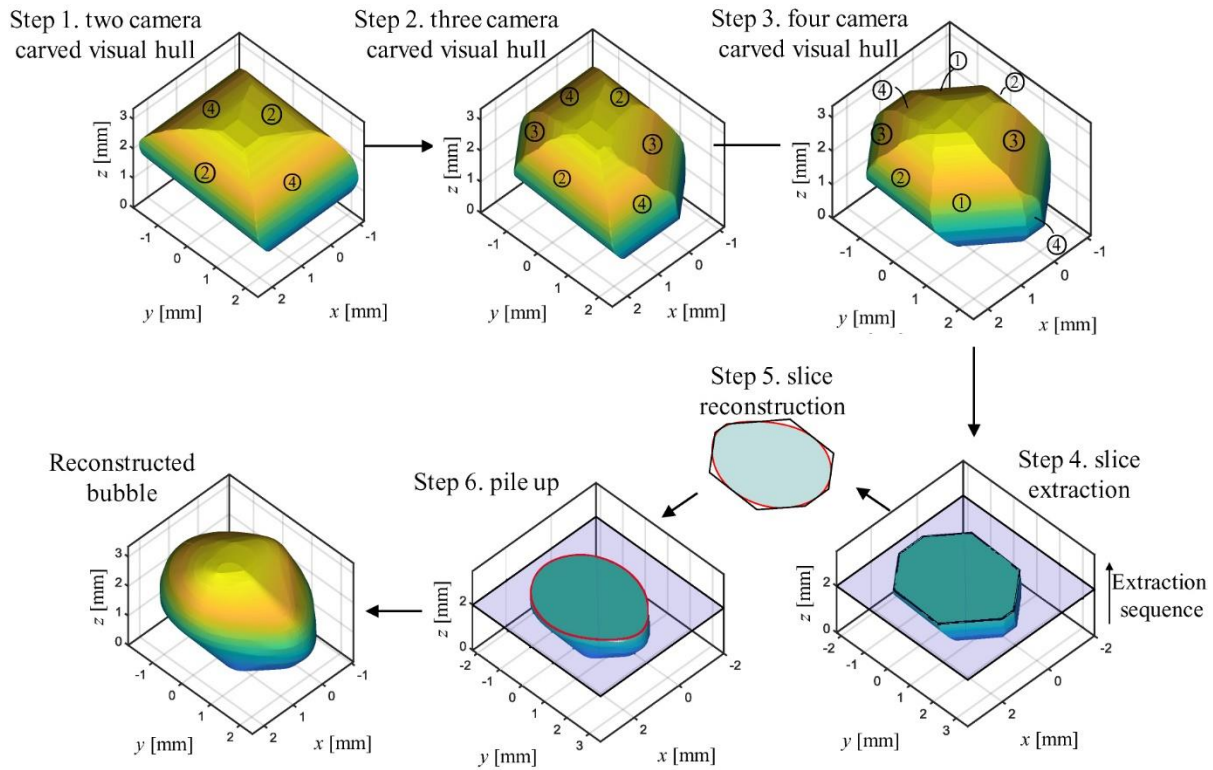


Fig. 4.9 The steps of implementing space-carving method with four high speed cameras. The number in step 1 to step 3 represents the visual hull surface carved by the corresponding camera.

4.4 Benchmark with Synthetic Bubbles

To evaluate the accuracy of different reconstruction algorithms discussed in the previous section, two different synthetic bubbles are generated. The shape of these two bubble types is visualized in Fig. 4.10. Both types are derived from simple ellipsoidal bubble model. Type A bubble has an oblate shape with a same semi-axis in the x and y directions, *i.e.*, $a = b = 2$ mm. The shorter semi-axis c is 1 mm. This oblate shape is usually used to model bubbles in the so-called distorted bubble regime [53,66,67]. In a more complicated case, a distorted bubble can be modeled by the combination of two semi-spheroid shapes with different short semi-axis of c_+ and c_- [34,68]. Type B bubble used in this study is a more general version of this kind of bubble. In this model, all three semi-axes a , b and c could take different values for each half part as shown in Fig. 4.10 (b). Further, the bubble can rotate freely along three axes, so the three Euler angles may take non-zero values.

Six test cases are presented in this benchmarking step. Type A bubbles are used for the first 3 test cases and type B bubbles are used in the next 3 test cases. For slicing method with one camera, “F” represents the front camera and “S” represents the side camera. If a bubble rises in an infinite medium with no wall influence, the front or side camera should give a similar result. In this study, the differentiation of front and side cameras is to consider the existence of wall influence which could cause uncertainties in the 1-camera system. The first 2 test cases rotate type A bubble along x axis only to examine the wall influence on 1-camera system. For test cases 3 to 6, the rotation angles are generated randomly. The generated synthetic bubbles and their corresponding projections on each camera in test case 1 and 4 are visualized in Fig. 4.11. The cameras are placed in the same location as the experiment.

The benchmark results with the synthetic bubbles are shown in Table 4.1. It can be seen that the space carving method has the best overall accuracy for either type A or type B bubbles. Ellipse fitting method shows a very good accuracy for type A bubbles but has larger uncertainty for type B bubbles as compared to the space carving method. This may be explained by the fact that the ellipse fitting method approximates each projection with a regular ellipse function. Therefore, it may not work very well for type B bubbles, which are not regular ellipsoids. The two camera slicing method shows good accuracy with type A bubble but has a larger uncertainty for type B bubbles. For the 1-camera slicing method, both the front and side camera show large uncertainties and unstable predictions for either type of bubbles. If bubble rotation happens only along the x

axis as in case 1 and 2, the front camera will have larger projection area and the reconstructed bubble will overestimate bubble size. For the side camera, the reconstructed bubble volume decreases accordingly with an increase of rotation angle. This scenario can actually occur when the wall influence is significant, which will be discussed further in the next section. For type B bubbles whose semi-axes and rotation angles are more random, the one camera slicing methods show an error as high as more than 50%.

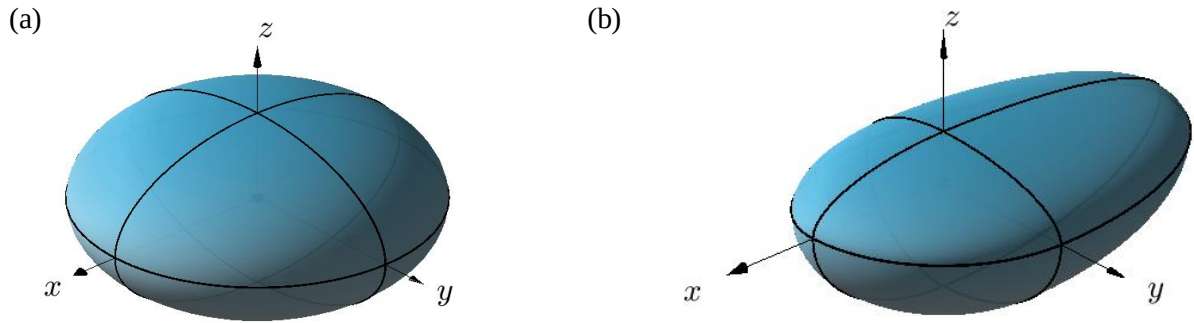


Fig. 4.10 Synthetic bubbles, (a) Type A: oblate shape bubble with $a = b = 2$ mm and $c = 1$ mm, (b) Type B: non-regular shape bubble with $a_+ = 1.5$ mm, $a_- = 2.5$ mm, $b_+ = 1.5$ mm, $b_- = 1$ mm, $c_+ = 0.5$ mm, $c_- = 1$ mm.

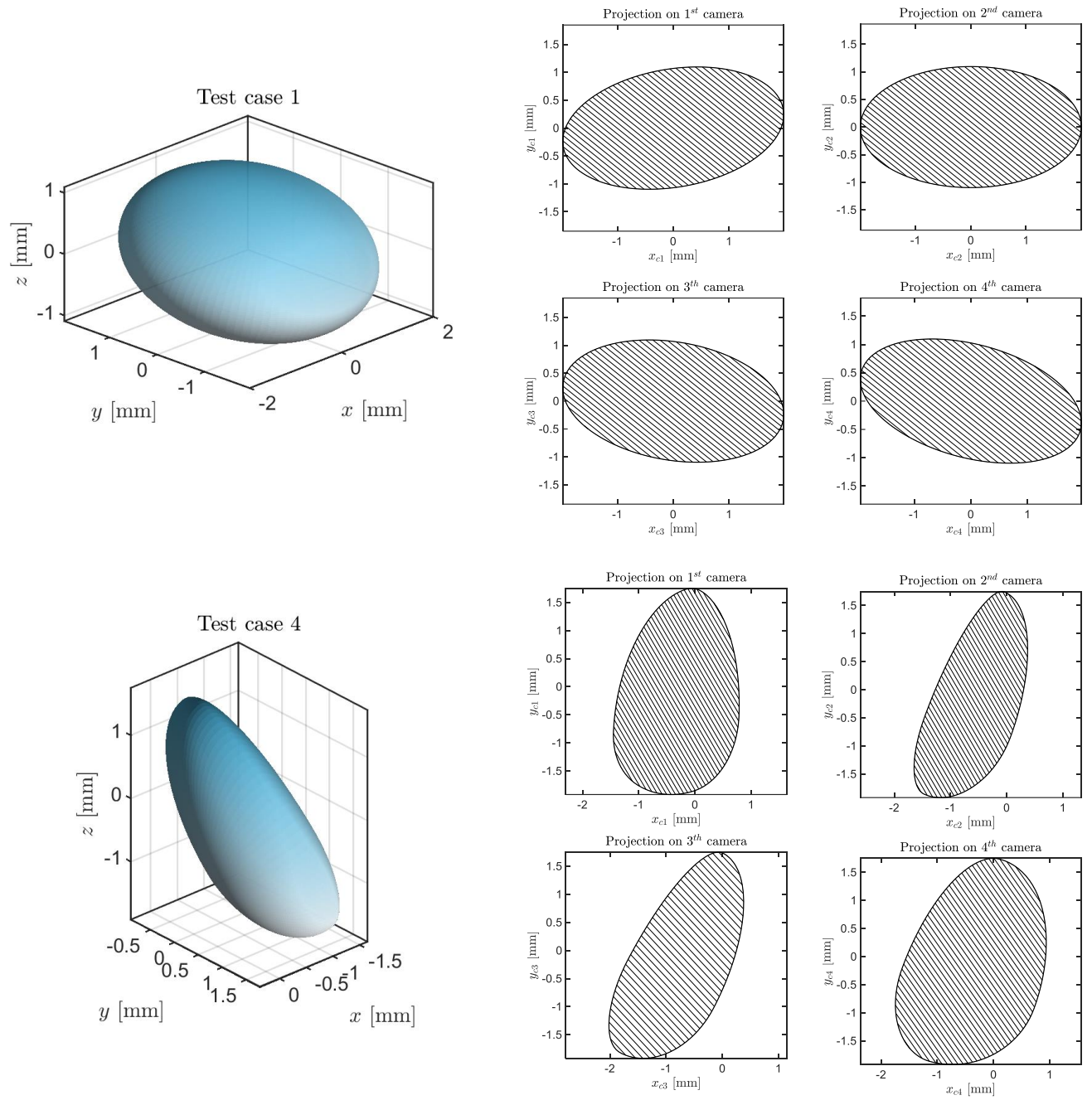


Fig. 4.11 Examples of synthetic bubbles used for test case 1 and 4, along with their corresponding projections on four high speed cameras.

Table 4.1 Test results with synthetic bubbles. Type A bubbles used in case 1-3, and Type B bubbles used in case 4-6.

Test case	Rotation angle			Space carving		Ellipse fitting		2-camera slicing		1-camera slicing (F)		1-camera slicing (S)	
	α	β	γ	Vol. [mm ³]	Error [%]	Vol [mm ³]	Error [%]	Vol [mm ³]	Error [%]	Vol [mm ³]	Error [%]	Vol [mm ³]	Error [%]
1	0	15	0	16.74	-0.07	16.71	-0.25	19.76	0.10	18.35	9.54	15.33	-8.49
2	0	30	0	16.87	0.68	16.68	-0.46	19.77	0.13	22.15	32.17	12.70	-24.21
3	-171	9	23	16.76	0.02	16.71	-0.25	19.72	-0.17	17.32	3.38	16.19	-3.40
4	-100	67	-106	8.15	3.80	8.29	5.56	9.50	-15.22	5.23	-33.43	12.58	60.12
5	151	-2	40	8.11	3.29	6.95	-11.48	9.62	3.70	12.28	56.36	5.44	-30.72
6	96	3	-73	8.34	6.16	7.26	-7.55	10.22	9.54	11.36	44.65	6.64	-15.42

4.5 Benchmark with Syringe Injection Tests

In experiment, the 3D imaging system recorded 331 bubbles. The total volume of these bubbles is 8845 mm³ based on the syringe readings. The reconstruction algorithms discussed in Section 4.3 are used for bubble reconstruction and volume measurement comparison. For each individual bubble, at least five consecutive frames are recorded in the imaging region. The bubble volume is calculated by averaging the reconstructed bubble volume over recorded frames.

Table 4.2 compares the accuracy of volume measured by these algorithms. It shows that the space carving method can measure the total bubble volume with an error of less than 2%. The ellipse fitting method overestimates the bubble volume by 10.62% and the 2-camera slicing method underestimates the bubble volume by 8.83%. For the 1-camera slicing method, the volume is overestimated by 27% if the front camera is used, whereas it is underestimated by 25.8% when the side camera is used. As can be seen, the front and side camera show considerably different results even with the same reconstruction algorithm.

Table 4.2 Comparison of bubble volume results obtained by five reconstruction algorithms.

Total volume [mm ³]	Bubble count	Space carving		Ellipse fitting		2-camera slicing		1-camera slicing (F)		1-camera slicing (S)	
		Volume [mm ³]	Error [%]	Volume [mm ³]	Error [%]	Volume [mm ³]	Error [%]	Volume [mm ³]	Error [%]	Volume [mm ³]	Error [%]
8845	331	8984	1.57	9784	10.62	8064	-8.83	11244	27.12	6561	-25.82

To further understand the difference in the volume measurement results, the trajectory of a single bubble over a sequence of frames is reconstructed using space-carving method as shown in Fig. 4.12 (a). The bubble is plotted every three frames, corresponding to a time interval of 12 ms. As can be seen, the bubble travels in a zigzag way along the z direction. The projections of the reconstructed bubble on the x - z plane and y - z plane are compared with the original images recorded by high speed cameras. These bubble images from different frames are stitched together into a single image to visualize the bubble motion. No obvious rotation along the y axis can be seen in Fig. 4.12 (b). In Fig. 4.12 (c), the bubble rotation along the x axis is observed, and the short semi-axis c tends to align with the moving direction of the bubble. After interaction with the left wall, the bubble changes its orientation and move along the opposite direction.

The bubble volume measured by different reconstruction methods at different frames are plotted in Fig. 4.13. Among these methods, the space carving, ellipse fitting and 2-camera slicing methods show relatively stable results. The 1-camera slicing method using either the front or side camera, shows large oscillations in the measured volume, which means the method is more sensitive to bubble shape and rotation angle. As seen in Fig. 4.12, the bubble shape is close to oblate ellipsoid and its rotation is mainly along the x axis. When the bubble rotates along the x axis, the front camera shows an overestimation of bubble volume and the side camera shows an underestimation. The error also depends on the rotation angle.

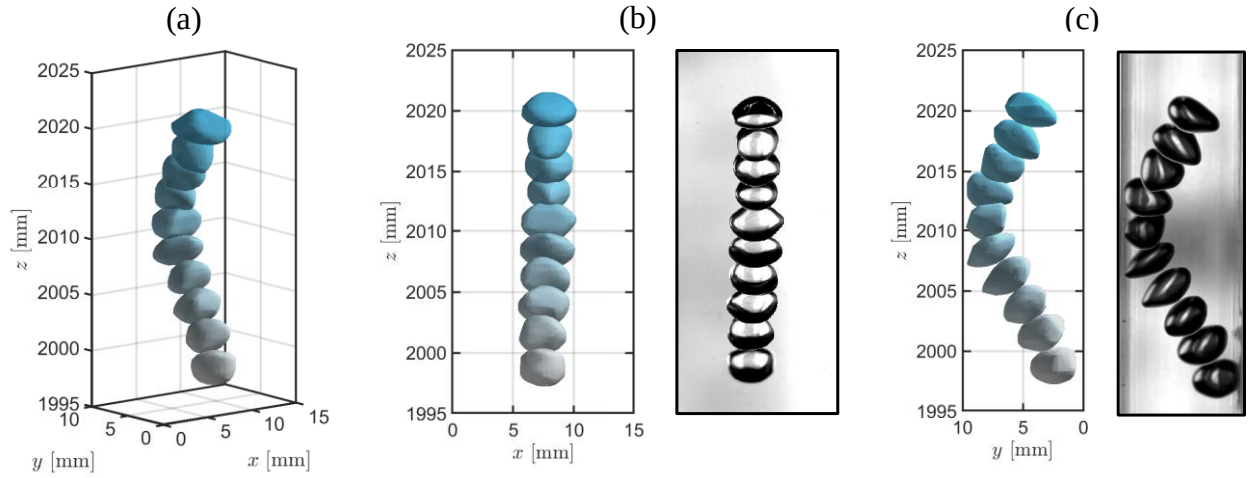


Fig. 4.12 (a) Visualization of a bubble in a sequence of frames in the rectangular channel. The bubble is visualized every three frames. (b) Comparison of bubble projection on the front camera. The bubble high speed images are stitched for comparison. (c) Comparison of bubble projection on the side camera. The bubble high speed images are stitched for comparison.

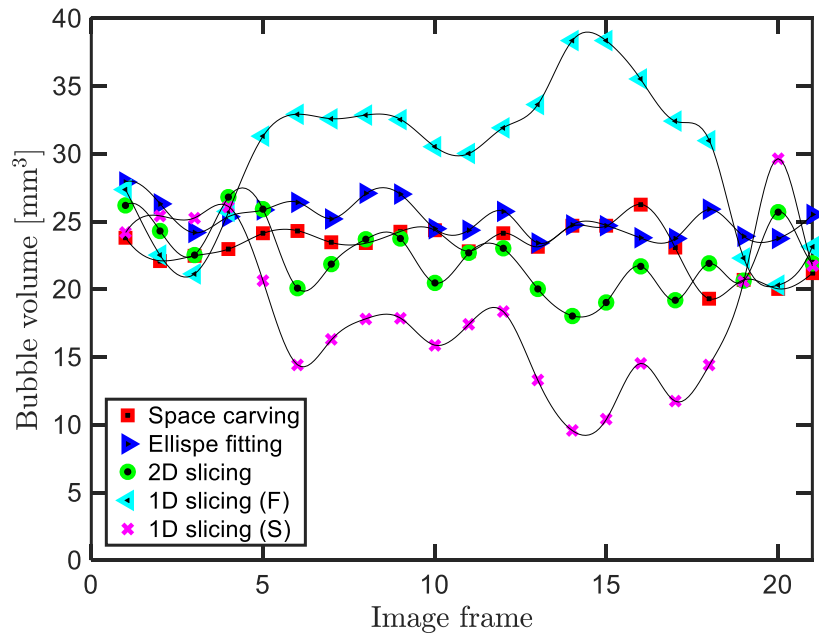


Fig. 4.13 Measurement of one gas bubble volume in a sequence of images with different bubble reconstruction algorithms.

To better access the accuracy of different methods in volume measurement, the variation in measuring the same bubble in different frames is quantified using the relative standard deviation defined as:

$$c_{v,i} = \frac{\sigma_i}{\mu_i}, \quad (4.18)$$

where σ_i, μ_i are the standard deviation and mean volume of the i^{th} bubble calculated from a sequence of frames. The results are shown in Fig. 4.14. The histogram of the relative standard deviation is obtained using all 331 bubbles. The 1-camera slicing method with front and side cameras have the averaged c_v of 0.20 and 0.27 respectively. Both show a more scattered c_v distribution compared with other methods. The slicing and ellipse fitting method with two cameras are more stable in measuring bubble volume with averaged c_v of 0.17 and 0.16, respectively. The space carving method shows a narrower distribution with an averaged c_v of 0.13. This indicates that the bubble rotation and shape changes have less influence on the volume measurement using the space carving method.

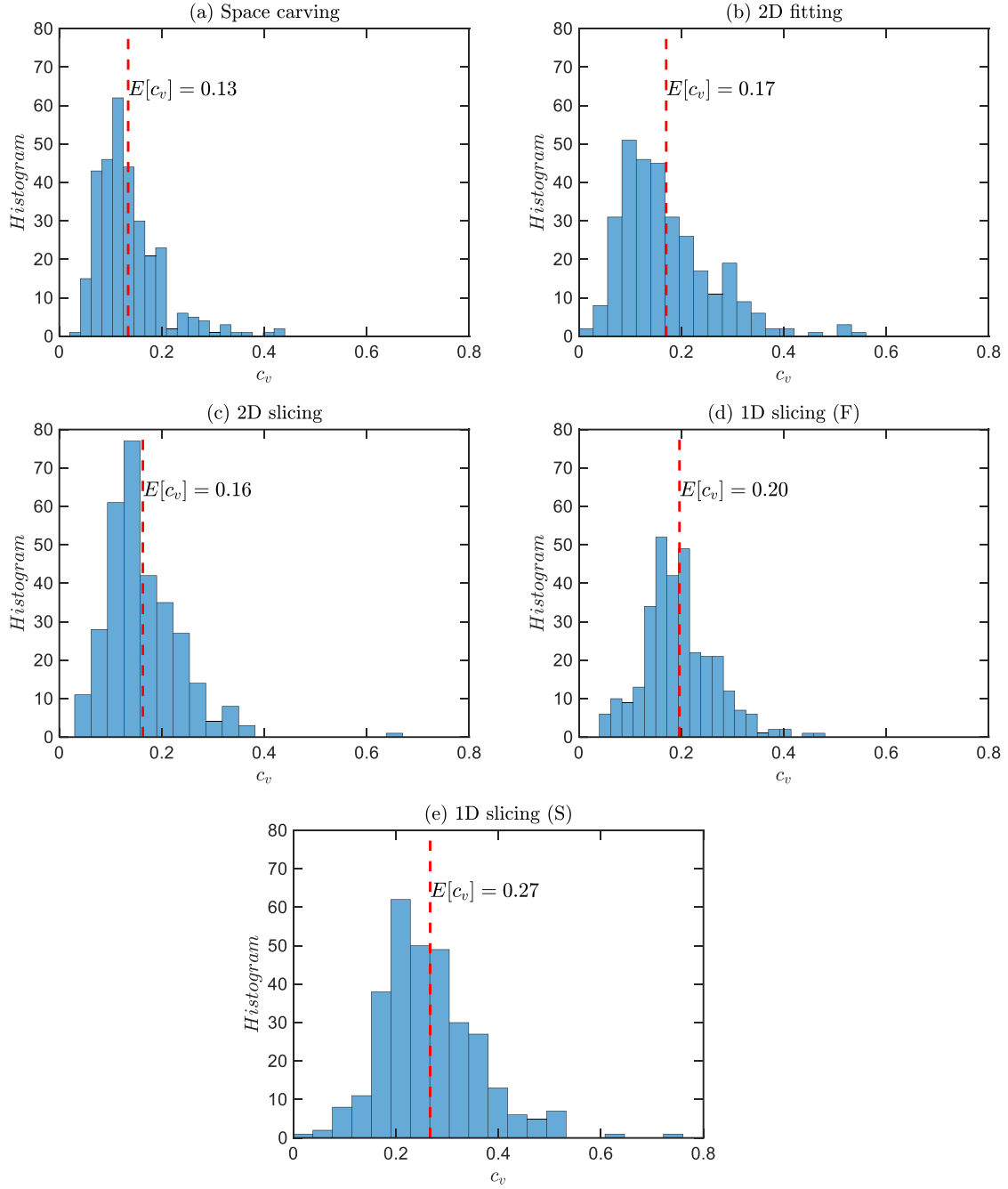


Fig. 4.14 Histogram of the relative standard deviation c_v using (a) space carving method, (b) ellipse fitting method, (c) 2-camera slicing method, (d) 1- camera slicing method (F) and (e) 1-camera slicing method (S).

4.6 Wall Influence on Bubble Rotation Angle and Aspect Ratio

With the development of the 3D imaging system and space carving method, bubble rotation angle and aspect ratio can be measured accurately. The details of bubble rotation angle and aspect ratio data measured are presented in this section. As mentioned in the experiment setup, the bubble injection is located at the center of the rectangular cross section. This setup results in a maximum probability of bubble appearing near the center location. Moving to four walls, the probability of bubble presence decreases. Fig. 4.15 shows the occurrence frequency of bubble location in the x - y plane. The distribution confirms the experiment setup of injecting bubbles at the center of the cross section.

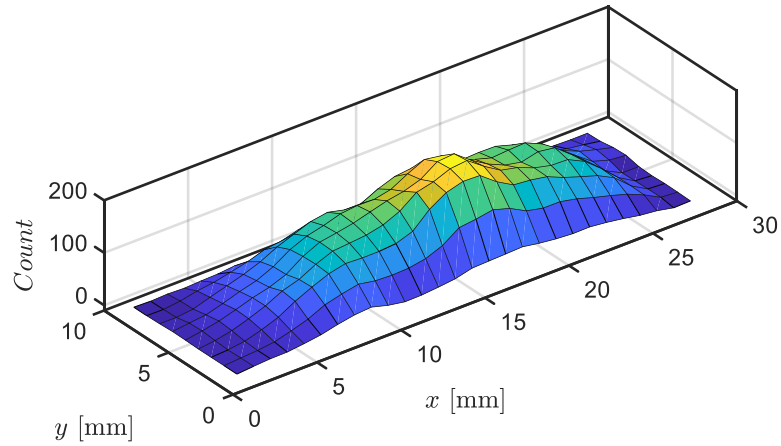


Fig. 4.15 The distribution of bubble count in the x - y plane.

To study bubble rotation, the bubble surface reconstructed by the space carving method is fitted with an ellipsoid function. The unit vector along the short semi-axis $\vec{n}_c$ obtained from the fitted ellipsoid is projected in the x and y directions for bubble rotation study. In Fig. 4.16 (a), the sketch shows an example with bubble rotates along the x axis only. The magnitude of the $\vec{n}_c$ projection on the y axis can be calculated as:

$$n_{cy} = |\vec{n}_c \cdot \vec{e}_y|, \quad (4.19)$$

where $\vec{e}_y$ is the unit vector along the y axis. The bubble rotation along the x axis is represented by n_{cy} . A larger rotation angle along the x axis will result in a larger n_{cy} value. The bubble rotation along the y axis n_{cx} is defined in a similar way as:

$$n_{cx} = |\vec{n}_c \cdot \vec{e}_x|, \quad (4.20)$$

where $\vec{e}_x$ is a unit vector along the x axis. The magnitude of n_{cx} is used to identify the bubble rotation along the y axis. Fig. 4.16 (b) shows an example of a rotated bubble with $\vec{n}_c$ projected both to x and y axis.

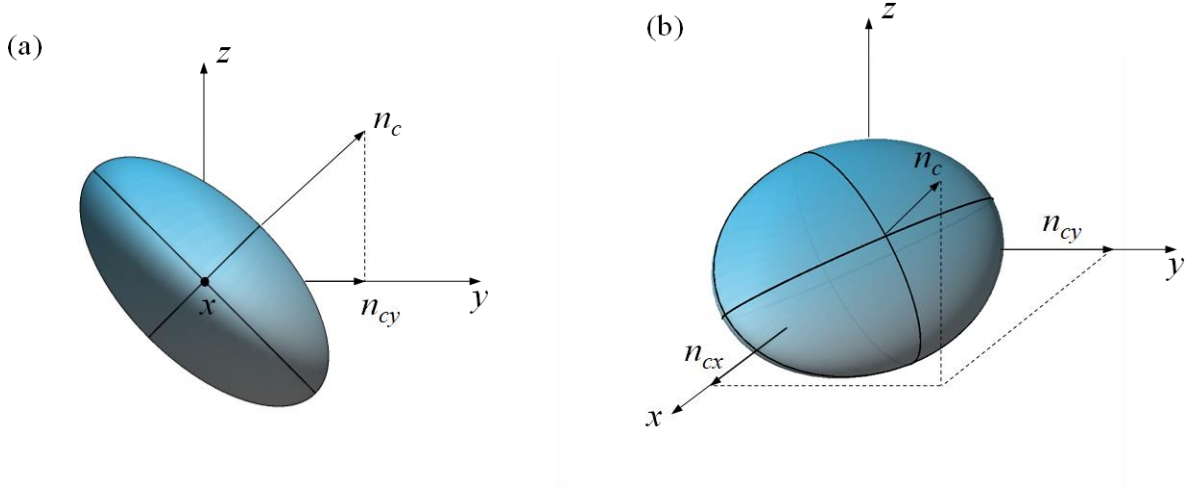


Fig. 4.16 Projection of the unit vector along the short semi-axis $\vec{n}_c$ in the x and y direction with (a) bubble rotation along the x axis only and (b) bubble rotation in a random direction.

The magnitude n_{cx} in the x direction and the magnitude n_{cy} in the y direction are shown in Fig. 4.17 (a) and (b), respectively. The results are averaged over all the bubbles that appeared in the corresponding region. Comparing Fig. 4.17 (a) and Fig. 4.17 (b), the results show that bubbles have more significant rotation along the x axis than along the y axis with a larger n_{cy} value. With the narrow gap, the bubbles have a higher frequency colliding with the front and back walls. This forces bubbles to rotate along the x axis, which is parallel to the front and back walls. The side wall influence in this case is limited because the distance of left and right walls are 30 mm apart, which is much larger than the 10 mm gap along the y direction. These factors explain that n_{cx} is generally smaller compared to n_{cy} in the entire test section.

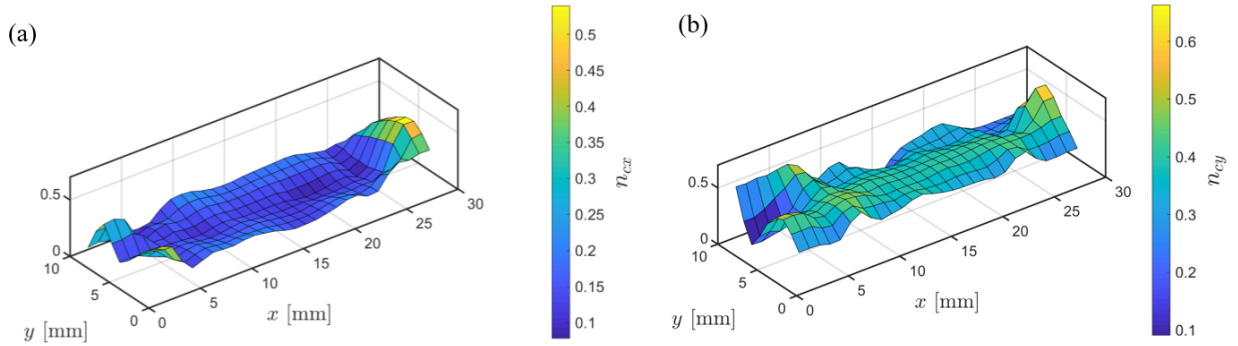


Fig. 4.17 The cross-section distribution of (a) the magnitude n_{cx} along the x direction and (b) the magnitude n_{cy} along the y direction

The aspect ratio distribution along the x and y axes are shown in Fig. 4.18. The results obtained from the space carving method are considered as the baseline values since they are less influenced by bubble rotation. Each data point represents the line-averaged aspect ratio along the y direction for Fig. 4.18 (a), and that along the x direction for Fig. 4.18 (b). The results obtained using only the front and side cameras are also shown in the figure. In this case, the aspect ratio is calculated using the ratio of the short to the long semi-axis of the fitted ellipse. With the existence of bubble rotation, the single-camera results show a higher aspect ratio compared with the spacing carving method. The aspect ratio obtained from the front camera is greater than that from the side camera. This can be explained by the greater rotation angle along the x axis compared to the rotation along the y axis.

As shown in Fig. 4.18 (a), the aspect ratio does not show a significant variation in the x direction for each method. Thus, the effect of two side walls is minimal to the bubble shape. As seen in Fig. 4.18 (b), the aspect ratio shows a strong dependence on the wall distance in the y direction. In the near wall region, a bubble will collide with the wall due to its finite size. This mechanism will squeeze the oblate shape bubble and make the bubble more spherical. This, in turn, increases the aspect ratio in the near wall region. After the collision, the bubble moves towards the center region and the bubble shape changes back to oblate. Hence, the aspect ratio decreases as bubble moves away from the wall. The wall effect on bubble aspect ratio change shows a similar trend as reported in the previous study by Hosokawa and Tomiyama [69].

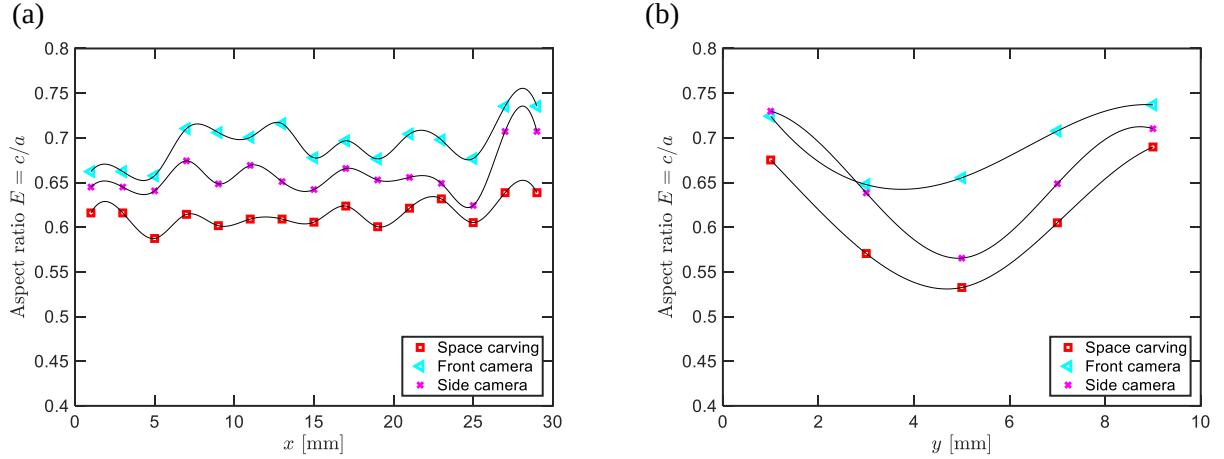


Fig. 4.18 Comparison of aspect ratio distribution obtained from the front camera, side camera and space carving method along the (a) x -axis and (b) y -axis.

In the literature, several studies [66,67,70] have shown that the bubble aspect ratio is closely related to the Eötvös number Eo , which is defined as:

$$Eo = \frac{\Delta\rho g d_v^2}{\sigma}, \quad (4.21)$$

where d_v , $\Delta\rho$, g , and σ represent the volume equivalent diameter, two-phase density difference, gravitational acceleration and surface tension, respectively. Wellek *et al.* (1966) proposed the following correlation for aspect ratio E :

$$E = \frac{1}{1 + 0.163 Eo^{0.757}}. \quad (4.22)$$

The correlation proposed by Okawa *et al.* (2003) is given as:

$$E = \frac{1}{1 + 1.97 Eo^{1.3}}. \quad (4.23)$$

Eqs. (4.22) and (4.23) are usually used as the upper and lower boundary for bubble aspect ratio estimation. Besagni and Inzoli (2016) used the data measured in a bubble column with a large annular gap and obtained the following correlation:

$$E = \frac{1}{1 + 0.553 Eo^{0.266}}. \quad (4.24)$$

The predicted aspect ratio falls in-between the values given by Wellek and Okawa. These three correlations are all based on the experimental data measured by a single camera system. A comparison of aspect ratio measured in this study using the space carving method with these

correlations is given in Fig. 4.19. The blue dots in the figure represent all the measurements for every bubble across all the recorded frames. The figure shows that most of the data points fall within the boundaries given by Wellek and Okawa. The scattered triangles, crosses and squares are the averaged aspect ratio results from the front camera only, side camera only and space carving method, respectively. The front camera results show a higher aspect ratio compared to the Besagni correlation since it did not record the bubble rotation along the x axis. By using the side camera alone, the imaging condition is similar to the large annular bubble column used in Besagni's experiment. The aspect ratio results obtained using the side camera show a very good agreement with the Besagni's correlation. However, the aspect ratio from either the front or the side camera is over-estimated due to the rotation in both the x and y direction. The red squares are the aspect ratio results obtained from the space carving method. It can be seen that the actual bubble aspect ratio should be smaller than the aspect ratio measured by a single-camera system.

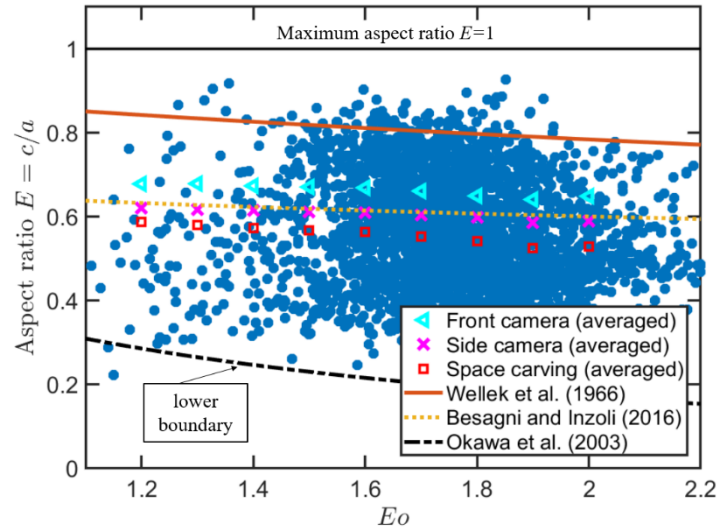


Fig. 4.19 Comparison of bubble aspect ratio correlations with experiment data. Blue dots represent data obtained by the space carving method for bubbles captured in all frames. The red squares are averaged data from space carving method. The cyan triangles and magenta crosses represent the averaged data from the front and side camera, respectively.

4.7 Summary

In this chapter, different methods to reconstruct 3D bubble shape, and measure bubble volume and surface area based on optical images are compared. When only one high speed camera or view angle is available, the bounding box can be used which extracts the width and height of the bubble projection. The 1-camera slicing method can estimate the bubble volume by assuming a circular cross section at every slice perpendicular to the image plane. Ellipse/ellipsoid fitting and 2-camera slicing method can be used to reconstruct the bubble if two views are available. The space carving method is proposed when more than two views are available for bubble reconstruction.

A 3D imaging system employing four high speed cameras is used to record images of bubbles in a 3 cm × 1 cm rectangular channel. A total of 331 bubbles, each being recorded in at least 5 frames are obtained in the test. The images are then processed using the different 3D bubble reconstruction methods. The space carving method shows the best agreement (less than 2% error) with the volume measured by syringe. It also shows the smallest variance in measuring the same bubble in a sequence of frames. The 2-camera based method including ellipse fitting and slicing can reach an accuracy of about 10% error. However, the 1-camera slicing method has a volume measurement error greater than 25%. The benchmarking study with synthetic bubbles shows a similar trend as the experimental data.

Though four cameras are used in this study, the space carving method described in the chapter is very generic and can be adapted to a system with even more cameras. With the increase of cameras, measurement accuracy is expected to be improved. However, the cost of the system also increases, so do the complexities in camera installation, calibration, and image storage and processing. In many applications, an imaging system with only one or two cameras is probably the only available option. This study shows that simple imaging system may achieve a reasonable result in certain conditions. In general, the 2-camera system can be used to acquire 3D bubble information with an error of about 10% compared with a 4-camera system. When image resolution is low, the ellipse fitting algorithm can do a good job for bubble shape estimation compared to space carving method, which requires more accurate bubble projection shape and camera position benchmark. For 1-camera system, the uncertainty is mainly from the bubble rotation and deformation caused by the wall influence and turbulence. In high Morton number and low

turbulence intensity conditions, the 1-camera system can yield reasonable results since the bubble deformation is less significant.

5 Bubble Generative Adversarial Networks (BubGAN)

5.1 Introduction

Dense object detecting and counting is a common but time-consuming and challenging task. In bubble column or nuclear reactor applications, accurate separation and reconstruction of bubble shape have equal importance to the number counting, since bubble shape contains important geometrical information for the study of mass, momentum and energy transport in these systems [71,72]. The demand for bubble shape acquisition introduces additional challenges for algorithm development and benchmarking in this field.

Along with the image processing algorithms proposed in this dissertation, many existed works has also been done [16,27,74–76,29–31,33,37,38,46,73] to deal with complicated bubbly flow conditions with high void fraction, severe bubble deformation and overlapping, etc. These algorithms can reduce the cost of processing bubbly flow images considerably and provide detailed information about bubble size distribution, shape, volume, etc. One issue in developing these algorithms is the way to benchmark the accuracy of these algorithms. Currently, the benchmark strategies can be divided into two categories. The first one is to compare the algorithm with different measurement techniques, which include conductivity probe [6,77], x-ray [12], or global gas and liquid flow meters. The benchmark with global instruments provides an overall error estimation without local uncertainty information. The comparison with conductivity probe or x-ray method can be made for time- or line-averaged parameters. The other issue in this benchmarking strategy is that these measurement methods may contain large uncertainty and may not be used to assess image processing algorithms [6].

The second strategy is to use synthetic images as the benchmarking data [37,39]. With the automation of image synthesizing process, the cost and time for the benchmarking of image processing algorithm can be reduced. The primary error source for this method comes from the gap between the real bubbly flow images and the synthetic ones. Current algorithms for synthetic images are mostly limited to generating simple bubble shapes such as spherical or elliptical bubbles. These physical models usually assume the bubble edge intensity follows a concentric circular/elliptical arrangements (CCA) [78,79]. With given bubble size and distribution information, synthetic bubbly flow images can be generated for benchmarking purpose. However, these algorithms are not capable of modeling fine structures of bubble shapes and intensity

variations. Synthetic bubbles of different size can have a similar intensity distribution. Therefore, image processing algorithms benchmarked with these synthetic images can have quite different performance in processing real bubbly flow images.

Conventional image processing algorithms are mostly based on certain features of bubble images such as curvature, intensity gradient, and topology information. The feature design and selection require the expertise in the related field to achieve an optimized performance. The deep learning algorithms such as convolutional neural networks (CNN), which do not require the input of extracted features from images, can be an alternative solution for bubble detection [79,80]. The CNN can process bubbly flow image in their raw form without pre-processing for number density detection. For those supervised deep learning algorithms, labeled images are required for algorithm training. Presently, the researches in using deep learning algorithm for bubbly recognition and separation in the chemical and nuclear engineering fields are limited. One of the bottlenecks is the lack of a large amount of high-quality labeled data for algorithm training. In other fields, using synthetic data becomes a trend for training deep networks to reduce the manual labeling cost and to improve the efficiency. However, this can be effective only if we can generate synthetic data which is close to the real world [81].

To bridge the gap between real bubbly flow images and synthetic ones, a new approach called bubble generative adversarial networks (BubGAN) is proposed in this chapter for generating realistic bubbly flow images. Conventional GAN algorithms can generate realistic images but they have no label information of these bubbles. In addition, the resolution of the generated images with GAN is relatively low compared to the recorded high-resolution images from high speed cameras. To overcome these shortcomings, the proposed BubGAN algorithm adopts the “divide and conquer strategy” to achieve high resolution labeled image generation. The BubGAN combines the conventional image processing algorithms [37,38] and the generative adversarial networks [82,83] for realistic bubble synthesis. In the algorithm, the GAN will be only responsible for single bubble generation rather than generating the bubbly flow images directly. The image processing algorithm is responsible for GAN training data preparation and bubble assembling for bubbly flow image synthesis. With given bubbly flow boundary conditions, the synthetic bubbly flow images can be generated by assembling single synthetic bubbles on an image background canvas. In these images, bubble location, edge boundary, rotation, etc., of all bubbles will be labeled for either existing algorithm benchmarking or development of new algorithms.

This chapter will first introduce the methodologies used in the BubGAN are introduced. A million-bubble database is generated for bubbly flow image synthesis with the BubGAN algorithm. Then, both qualitative and quantitative studies of the BubGAN are presented in this chapter to demonstrate its applications.

5.2 Methodology

This section presents the methodologies used in the BubGAN for the generation of synthetic bubbly flow images. As shown in Fig. 5.1, the BubGAN algorithm consists of three major steps. The first step is to process the recorded high-speed images to extract single bubble images. The second step trains a conditional GAN to generate synthetic bubble images based on the training data acquired from the previous step. This deep convolutional generative adversarial neural network (DCGAN) is conditioned on four selected bubble features, which are of primary interest in bubbly flow study. This enables the users to generate a specific bubble with given parameters for different flow conditions. To reduce the runtime cost, a million-bubble database is pre-generated based on the trained conditional GAN. With given bubble size distribution and other related physical information, synthetic bubbles can be directly sampled from the million-bubble database and be assembled to generate synthetic bubbly flow images. The tool for synthetic bubbly flow image generation is available at <https://github.com/ycfu/BubGAN>.

In these steps, two primary techniques, namely, image processing and conditional GAN are used in the BubGAN algorithm. As shown in Fig. 5.1, the processes associated with image processing techniques are shown in red, and those with conditional GAN in purple. The blocks marked in blue represent the physical information required for bubbly flow image generation, and the yellow blocks represent the data used in the BubGAN.

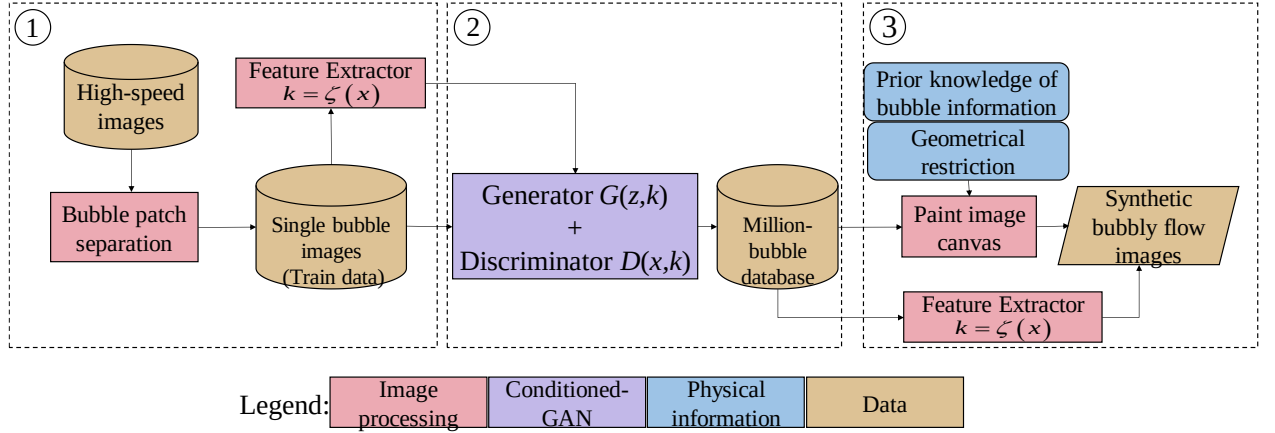


Fig. 5.1 The pipeline of the BubGAN algorithm. The three major steps consist of bubble training data extraction, million-bubble database generation with conditioned-GAN and bubbly flow image synthesis with given physical information. The legends represent the primary techniques and information used in BubGAN.

5.2.1 Image Processing Technique

Various image processing tasks have been performed throughout the BubGAN workflow. To train the GAN algorithm, a sufficient amount of real bubble samples should be prepared. The bubbly flow images were first segmented into small image patches which either contain a single bubble or a number of bubbles which are connected together. For each image patch, three different algorithms, namely, watershed segmentation, bubble skeleton and adaptive threshold methods are used to determine whether this patch contains only a single bubble. The detailed procedures with sample intermediate results are shown in Fig. 5.2. Each algorithm will give a prediction of bubble number in the patch as denoted as N_1 , N_2 , N_3 , respectively. Then the combined number prediction N is assigned as the modal value N_1 , N_2 and N_3 . Once a patch is identified as a single bubble, it will proceed to visual checking step for results confirmation. In this study, 10000 single bubble image patches are extracted from the bubbly flow images. The used bubbly flow images are from the port 1 in run 1 as described in Chapter 3.

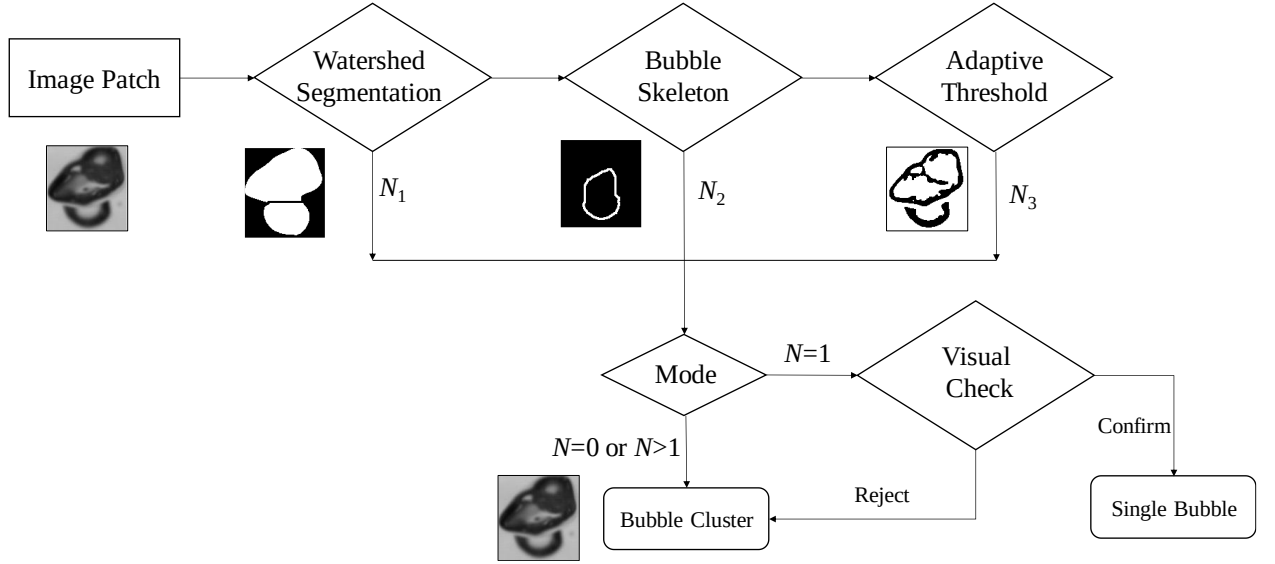


Fig. 5.2 The flowchart of identifying single bubble and bubble cluster patches. The process involves watershed segmentation, bubble skeleton and adaptive threshold methods for bubble number prediction in an image patch. Visual checking will be applied before a patch is finally classified as a single bubble. The figure also includes a sample image patch, which is classified as a bubble cluster.

After classification, all single bubble patches are further processed and normalized to serve as the training data for GAN. These steps are summarized graphically in Fig. 5.3. An example of a separated bubbly flow image is shown in Fig. 5.3 (a). The bubble cluster and single bubble patches are separated by the aforementioned algorithms. Those single bubbles are cropped by a square window for further processing. This will ensure that the aspect ratio of the bubble is preserved in the following normalization process. In these patches, other bubble fragments may appear as shown in Fig. 5.3 (b). To remove these fragments, the grayscale bubble image is converted to a binary image as shown in Fig. 5.3 (c). The fragment can be identified using the binary image and it is removed by filling the region with the background. The bubble mask and single bubble image after noise removal are shown in Fig. 5.3 (d) and Fig. 5.3 (e), respectively. Each separated single bubble patch is then normalized and rescaled to a size of 64×64 pixels for the GAN training in the next step.

In addition to training data preparation, image processing algorithm is also used in a later step for bubble feature extraction and bubbly flow image assembling. The details of the image processing technique have been described in Chapter 2.

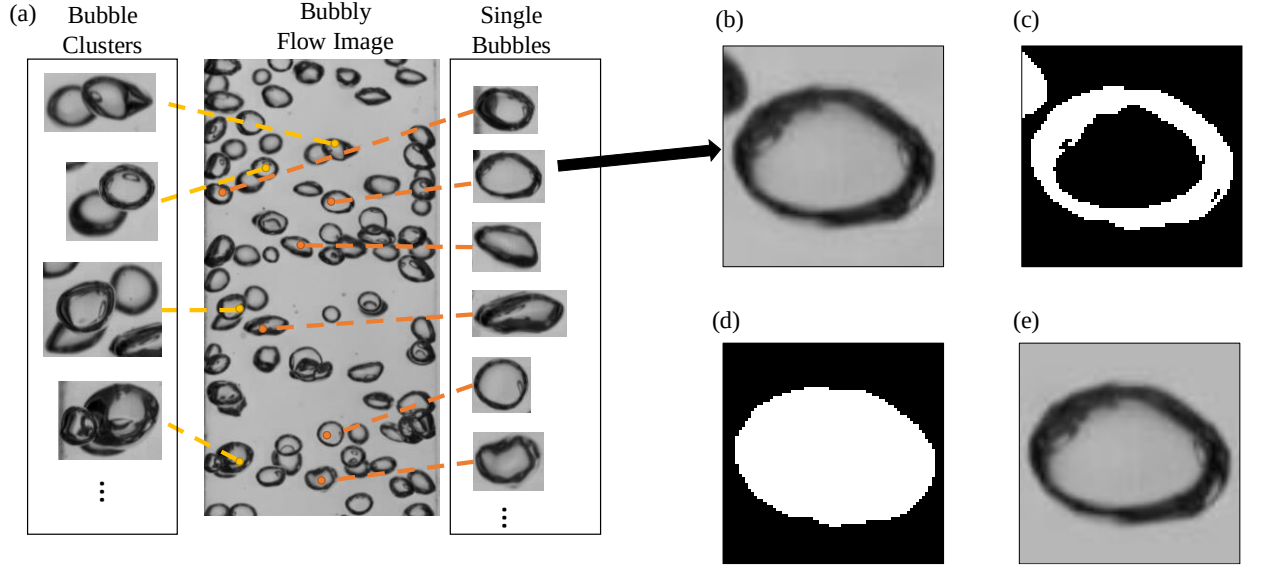


Fig. 5.3 Procedures of separating single bubble images using the bubbly flow image processing algorithm (a) separate the single bubbles and bubble clusters from the recorded bubbly flow images, (b) extract square single bubble patch from image, (c) binarization of the grayscale bubble image, (d) remove noise and partially cropped bubble (e) normalized single bubble image.

5.2.2 Bubble Feature Extraction

Four parameters related to bubble geometry and topology are of primary interest in this study. These parameters are selected such that they can characterize typical bubbles during their transport processes in engineering applications. These parameters often appear in the engineering models or correlations. In addition, they will be used as one metric to assess the quality of the synthetic bubble images in a later section.

The first parameter is the bubble aspect ratio E , which is defined as:

$$E = \frac{b}{a}, \quad (5.1)$$

where a and b are the semi-major and semi-minor axes of the ellipse fitted on the bubble. The second parameter is the rotation angle φ which is defined as the angle from the positive x axis to the semi-major axis in an anti-clockwise direction. The third parameter Ψ is called the circularity of the bubble, which is calculated as:

$$\Psi = \frac{4\pi A}{P^2}, \quad (5.2)$$

where A represents the bubble projection area and P stands for the perimeter of the bubble. If the bubble is close to a circle, Ψ will be close to 1. If the bubble is elongated or has an irregular shape, Ψ decreases towards 0. The fourth parameter, edge ratio m , is defined as the dark edge area A_{edge} over the bubble projection area A as:

$$m = \frac{A_{edge}}{A}. \quad (5.3)$$

This parameter can be used to represent bubble appearance. The darker edge corresponding to more total reflection, which can be caused by stretching bubble along the camera axis. In this case, the m will have a large value. If the bubble is stretched in the two directions perpendicular to the camera axis, there will be less total reflection area and the m will be close to 0. Besides, the setup of the backlit illumination and bubble surface distortion can also be factors which affect value of m .

A summary of these parameters are listed in Table 5.1. The range and unit of these parameters are given in the table. It should be noticed that the ranges in the table give the minimum/maximum possible values for reference. In real bubble images, the parameters may not reach the extreme value.

Table 5.1 Description of extracted bubble feature parameters.

Bubble parameter	Definition	Range	Unit
Aspect ratio E	$E = b/a$	(0,1]	-
Rotation angle φ	Rotation of the fitted ellipse on the bubble image	$(-\pi/2, \pi/2]$	Rad
Circularity Ψ	$\Psi = 4\pi A / P^2$	(0,1]	-
Edge ratio m	$m = A_{edge} / A$	(0,1]	-

5.2.3 Generative Adversarial Networks

The generative adversarial networks [82,83] is used for the generation of realistic single bubble images in this work. The GAN consists of two different neural networks, namely, the generative network defined by a function G and the discriminator network defined by a function D . The discriminator function $D(x)$ takes an input of x , which represents the images used for training or testing. In this study, x consists of 10000 training bubble patches extracted from the high speed images taken in bubbly flow condition. The discriminator network D does the classification job for identifying the real bubbles and the synthetic bubbles generated by the generative network G . The generative network would generate images using function $G(z)$, where z is the latent vector sampled from a prior normal distribution. The terms $\theta^{(D)}$ and $\theta^{(G)}$ are the parameters used in function D and G . With the cross-entropy cost definition, the discriminator cost function is defined as:

$$L^{(D)}(\theta^{(D)}, \theta^{(G)}) = -\frac{1}{2} \mathbb{E}_{x \sim p_x} \log D(x) - \frac{1}{2} \mathbb{E}_{z \sim p_z} \log(1 - D(G(z))). \quad (5.4)$$

The cost function of the generator can be directly calculated as:

$$L^{(G)} = -L^{(D)}, \quad (5.5)$$

in a zero-sum game. To reach the Nash equilibrium of the game, one should optimize the parameters with the minimax of:

$$\arg \min_{\theta^{(G)}} \max_{\theta^{(D)}} L^{(G)}(\theta^{(D)}, \theta^{(G)}). \quad (5.6)$$

In this work, the deep convolutional generative adversarial network [83] is adapted for bubble image generation due to its improved quality and sharpness in image generation. To have better control of the generated bubble images, both the generative and discriminator networks are conditioned on the bubble features for training. The detailed structure of the proposed conditional GAN is illustrated in Fig. 5.4. As shown in the figure, the input of a generative network consists of a bubble feature vector $k \in \mathbb{R}^4$ and a random latent noise vector $z \in \mathbb{R}^{100}$. The bubble feature vector k contains four bubble parameters as summarized in Table 5.1:

$$k = \zeta(x) = [E, \phi, \Psi, m]. \quad (5.7)$$

where $\zeta(x)$ represents the feature extractor function based on the image processing algorithm.

After convolution, the feature vector is projected to 512 dimensions and concatenated in depth to both the Generative network G and the discriminator network D . With the feedback given by

the discriminator, the generator G can finally learn to generate the realistic bubble images with its feature given by the feature vector k . The output bubble image from G has a dimension of $64 \times 64 \times 3$.

In the training process, the conditional GAN should be able to achieve two objectives. For the generator G , it should be able to generate bubbles with features defined by input feature vector k . For the discriminator D , it should be able to identify whether the feature vector k matches the input bubble along with identifying the authenticity of the bubble image. To reinforce the connection between a bubble and its feature vector, three types of false pairs are designed for training the discriminator D . The first is using a fake image $\hat{x}$ with its corresponding input feature vector k_2 . The second pair is the fake image $\hat{x}$ paired with an incorrect bubble feature vector k_3 . The third pair is a real bubble image x paired with an incorrect bubble feature vector k_2 , which is used for the synthetic image generating. Then the loss function for the discriminator can be updated as:

$$L^{(D)} = -\frac{1}{2} \mathbb{E}_{x \sim p_x} y - \frac{1}{2} \mathbb{E}_{z \sim p_z} \left[\frac{1}{3} \log(1 - \hat{y}_1) + \frac{1}{3} \log(1 - \hat{y}_2) + \frac{1}{3} \log(1 - \hat{y}_3) \right], \quad (5.8)$$

where $\hat{y}_1 = D(\hat{x}, k_2)$, $\hat{y}_2 = D(\hat{x}, k_3)$, $\hat{y}_3 = D(x, k_2)$, and $y = D(x, k_1)$ represents the score given by the discriminator with the input of real image x along with its feature vector k_1 . The details of training the networks are shown in Algorithm 1.

With the trained GAN conditioned on bubble features, a million bubbles are generated to create a database for bubbly flow image synthesis. These generated bubbles are preprocessed to get their companion feature vector k . The bubble feature information is associated with each bubble, which will allow a quick search of the desired bubble image given a feature vector input. This database will improve the efficiency of generating synthetic bubbly flow images to be discussed in the coming steps.

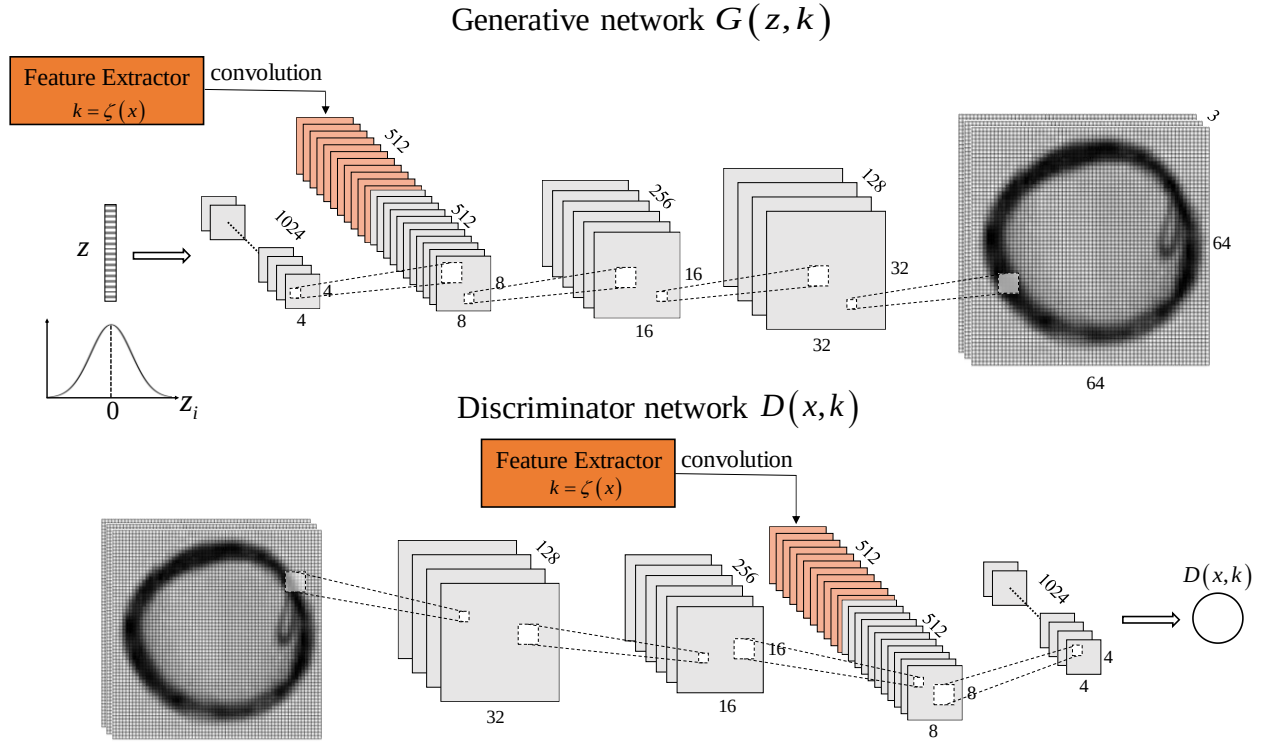


Fig. 5.4 The structure of proposed generative adversarial networks(GAN) conditioned on the bubble features.

Algorithm 1

for the number of training epochs **do**

for the number of minibatches **do**

1. $k_1 = \zeta(x)$ **Extract matching bubble feature vectors from minibatch images**
2. k_2, k_3 **Draw random bubble feature vectors from the training images**
3. $\hat{x} = G(z, k_2)$ **Generate fake images with the Generator network G**
4. $y = D(x, k_1)$ **Calculate a score for real image with matching feature vectors**
5. $\hat{y}_1 = D(\hat{x}, k_2), \hat{y}_2 = D(\hat{x}, k_3), \hat{y}_3 = D(x, k_2)$ **Generate fake inputs for the discriminator**
6. **Minimize** $L^{(D)} = -\frac{1}{2} \mathbb{E}_{x \sim p_x} y - \frac{1}{2} \mathbb{E}_{z \sim p_z} \left[\frac{1}{3} \log(1 - \hat{y}_1) + \frac{1}{3} \log(1 - \hat{y}_2) + \frac{1}{3} \log(1 - \hat{y}_3) \right]$
7. **Maximize** $L^{(G)} = \frac{1}{2} \mathbb{E}_{x \sim p_x} (1 - D(\hat{x}, k_2))$ **or equivalently minimize** $-\frac{1}{2} \mathbb{E}_{z \sim p_z} (D(\hat{x}, k_2))$

in practice

end for

end for

5.2.4 Physical Information and Geometrical Restriction

With given physical information, such as, bubble size and number density distribution, synthetic bubbly flow images can be assembled using the million-bubble database. In addition, geometrical restriction should be applied on bubbles to prevent them from going outside the physical boundary. The flowchart of generating upward bubbly flow images are shown in Fig. 5.5. In this process, the flow region and imaging area should be given as a prior. Bubble size distribution and void fraction distribution in the lateral direction together determine the averaged bubble occurrence frequency and size in the images. With this information, a bubble list can be created with known semi-axes (a, b) , location (x, y, z) , and aspect ratio E , etc. Based on this list, the million-bubble database will be searched to select the bubbles with matching parameters. Finally, these bubbles will be painted onto the image canvas according to their center locations (x, y, z) . Since the million-bubble database has a standard image size of 64×64 pixels, the bubble

image should be rescaled to the desired size specified by the bubble list for painting. As shown in Fig. 5.5 (d), when painting the bubble onto the image canvas, the flow boundary restriction should be enforced. In another word, any part of a bubble should not exceed the physical boundary of the flow channel. The numbered bubbles in Fig. 5.5 (d) are three typical scenarios when a bubble is partially outside the imaging area, where the left and right boundary lines also coincide with the physical boundary of the vertical flow channel. The first bubble will be shifted left to make sure the entire bubble is inside the physical boundary. For the second bubble, the lower part is partially outside the image boundary. However, the bubble is still within the physical boundary of the flow channel. Therefore, this part will just be cropped in painting. For the third bubble on the top-left corner, it will be shifted to the left first, then the upper part will be cropped to meet the geometrical restriction requirement.

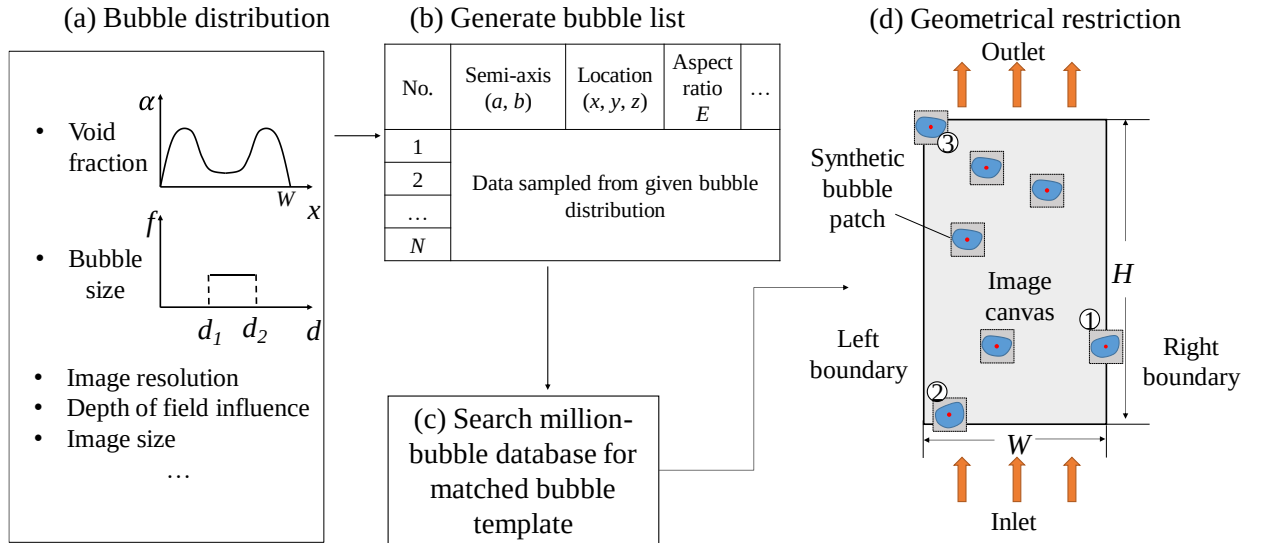


Fig. 5.5 Flowchart of generating synthetic bubbly flow images with the million-bubble database. Additional physical information such as bubble size and location distribution is given as priors. Geometrical restriction is applied to prevent bubbles from going outside the physical boundary of flow channel.

5.3 Results and discussions

5.3.1 Quantitatively Assessment of BubGAN

It becomes feasible to generate realistic bubbly flow images using the proposed BubGAN algorithm. To assess the diversity of the million-bubble database, two sets of synthetic bubbles sampled from the database are shown in Fig. 5.6. The first image collection shows bubbles with various aspect ratios and rotation angles. The second image collection shows bubbles with various edge ratios and circularities. It is seen that the million-bubble database contains bubbles with a large variance in bubble features. The abundant bubble shapes and appearances should be able to synthesize bubbles appeared in most bubbly flow conditions.

As discussed in Section 5.2, the GAN is conditioned on bubble features. The generator $G(x, k)$ can generate synthetic bubbles according to the given feature vector k . To check whether the generator G can reproduce correct bubble images, three tests are carried out with different feature vectors. The results are shown in Fig. 5.7. In the first test, bubble rotation angle is fixed at $\varphi_{Cond} = 0.53$ in the input vector k . Then a total of 64 bubbles are generated using the trained generator G . Among these generated bubbles, the averaged rotation angle is $\bar{\varphi}_{Gen} = 0.52$ with a relative error of 2.38%. The second and the third histograms show bubble aspect ratio and edge ratio distribution with given feature input of $E_{Cond} = 0.61$ and $m_{Cond} = 0.78$, respectively. The results show a relative error of less than 2% in both cases.

The above tests use statistical data to access the quality of the BubGAN, which is conditioned on bubble features. An exhaustive evaluation of the BubGAN performance on generating bubbles is shown in Fig. 5.8. In the evaluation, synthetic bubbles are generated by varying a specific parameter at a time. For example, Fig. 5.8 (a) shows an example of generating bubbles by varying rotation angle φ_{Cond} from negative to positive, which is shown along the x axis. The y axis represents the result $\bar{\varphi}_{Gen}$ obtained from the generated bubbles. Each data point in the figure represents the value averaged over 100 sample images. The root-mean-square error (RMSE) is calculated using all 10 data points for each parameter to assess the overall performance of the BubGAN. For all four feature parameters, the RMSE is less than 2.5%. This indicates that the generator G is capable of reproducing desired bubbles over a wide range of conditions.

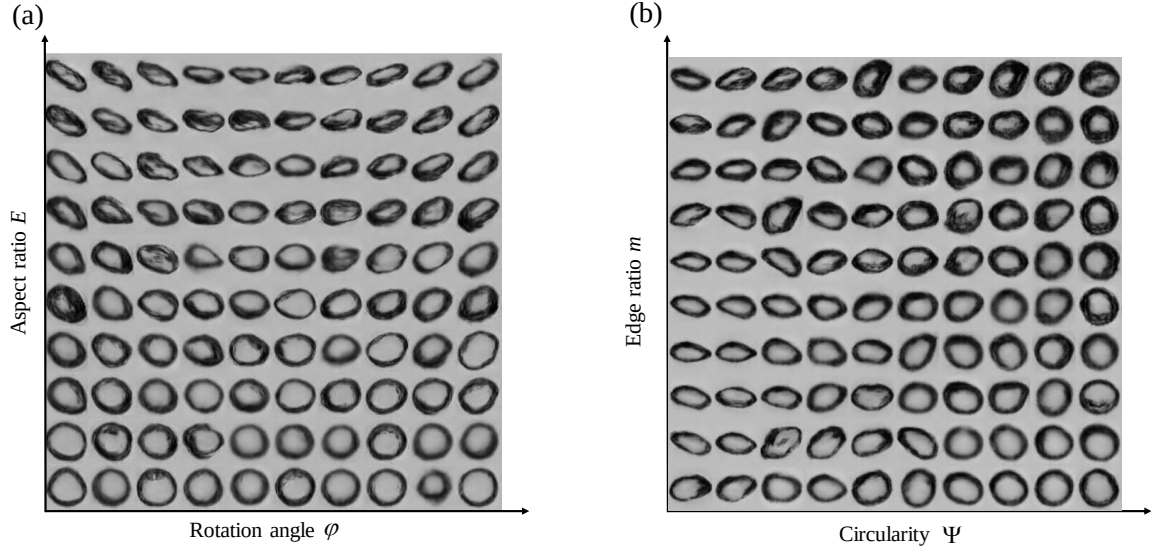


Fig. 5.6 Single bubble image samples selected from the million-bubble database with various features of (a) aspect ratio E and rotation angle, (b) edge ratio m and circularity.

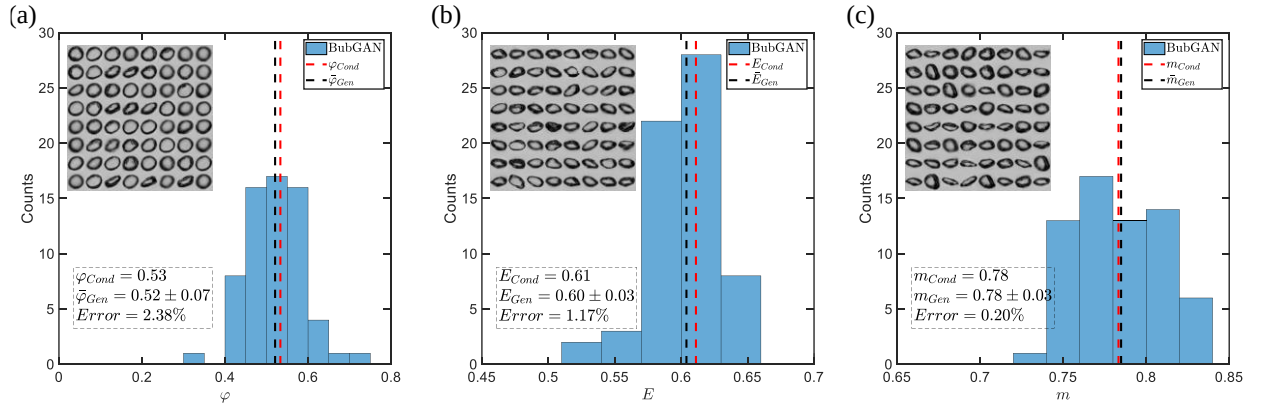


Fig. 5.7 A quantitative study of synthetic bubble generation conditioned on given bubble parameters of (a) rotation angle $\varphi_{Cond} = 0.53$, (b) aspect ratio $E_{Cond} = 0.61$ and (c) edge ratio $m = 0.78$.

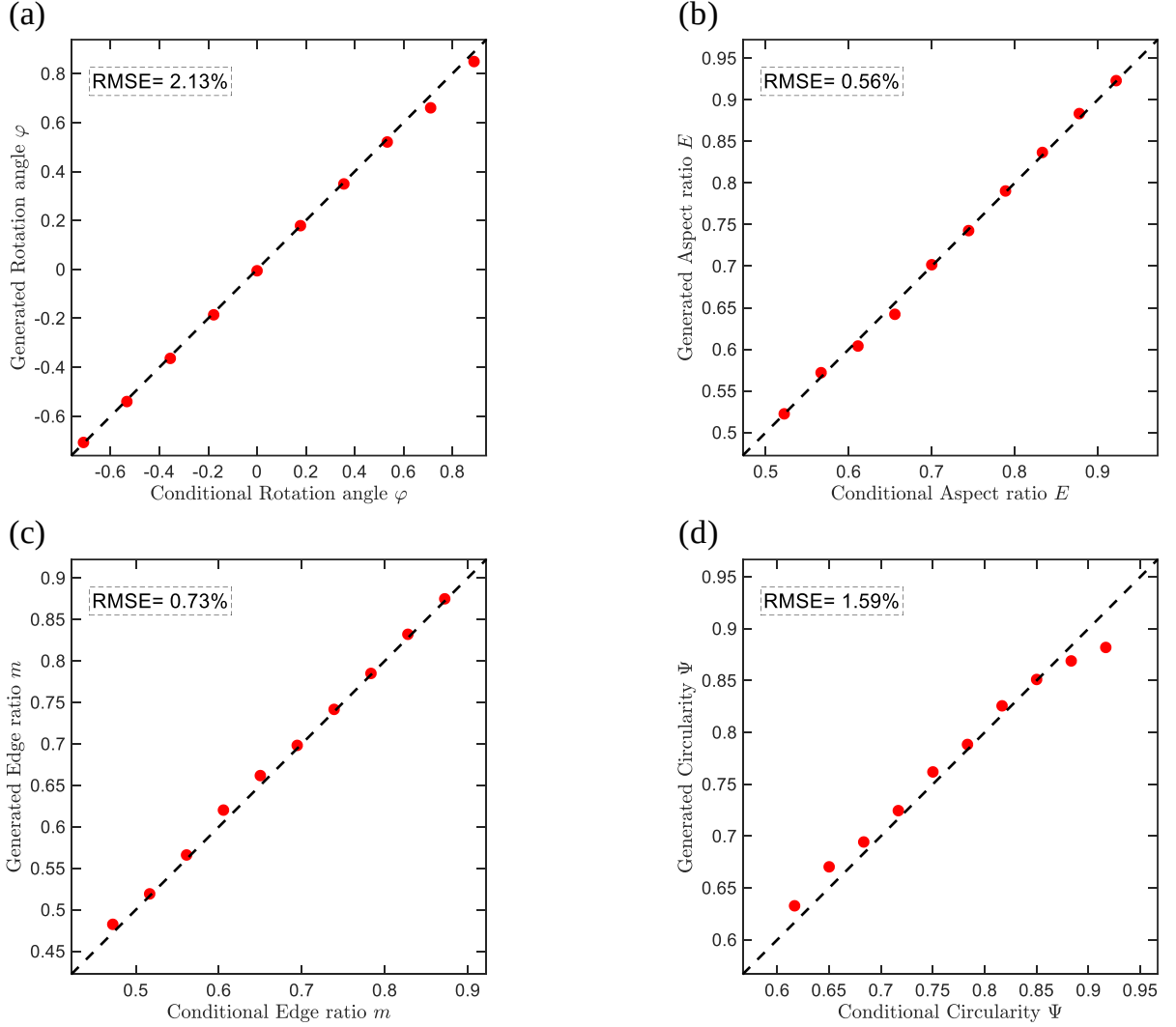


Fig. 5.8 Statistical evaluation of the conditioned GAN on generating the bubbles on given bubble parameters of (a) rotation angle, (b) aspect ratio, (c) edge ratio and (d) circularity. The root-mean-square error calculated from ten data points in each plot. Each data points are the averaged value calculated from 100 generated bubble samples with a given fixed bubble feature value.

It should be noticed that the input bubble feature vector k should be sampled from the training dataset. This is because the conditional GAN learns bubble features in the manifold of bubble feature space defined by the training dataset. A random combination of four bubble feature components can result in unphysical feature vector k , which will downgrade the image quality. The correlations among different feature parameters of the training dataset are shown in Fig. 5.9.

As shown in the figure, different parameters have a certain degree of correlation with other parameters. Therefore, the bubble feature vector k has a degree of freedom less than 4. In the generation of synthetic bubbles, the four feature components cannot be specified randomly without considering the potential correlations among them. To augment the feature vector space, interpolation of two feature vectors can be used to add variation of bubble shapes and appearances. This method has been proven to work well in deep representation mixing [84] and text to image synthesis [85]. In this work, a new bubble feature vector k is interpolated by combining two existing feature vectors (k_i and k_j) randomly sampled from the training dataset as:

$$k = \beta k_i + (1 - \beta) k_j, \quad (5.9)$$

where β can be a value from 0 to 1. With this interpolation, the newly generated bubbles show good quality and the feature vectors can match the input. An example is shown in Fig. 5.10 with five spider plots by varying β from 0 to 1. The blue lines in the figure represent the interpolated input feature vector, and the red dashed lines represent the actual values of generated bubbles. The results show a very good match between these two, which indicates that the trained generator G can generate bubbles with an arbitrary feature vector within the convex hull formed by the training dataset.

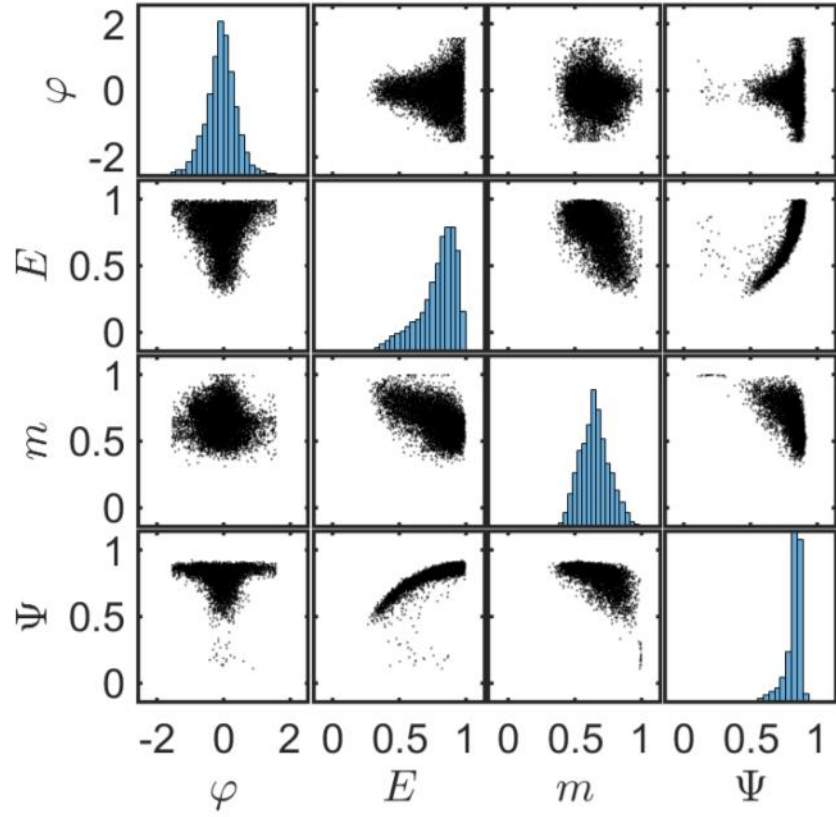


Fig. 5.9 A matrix plot of the correlations between four bubble features acquired from the training data.

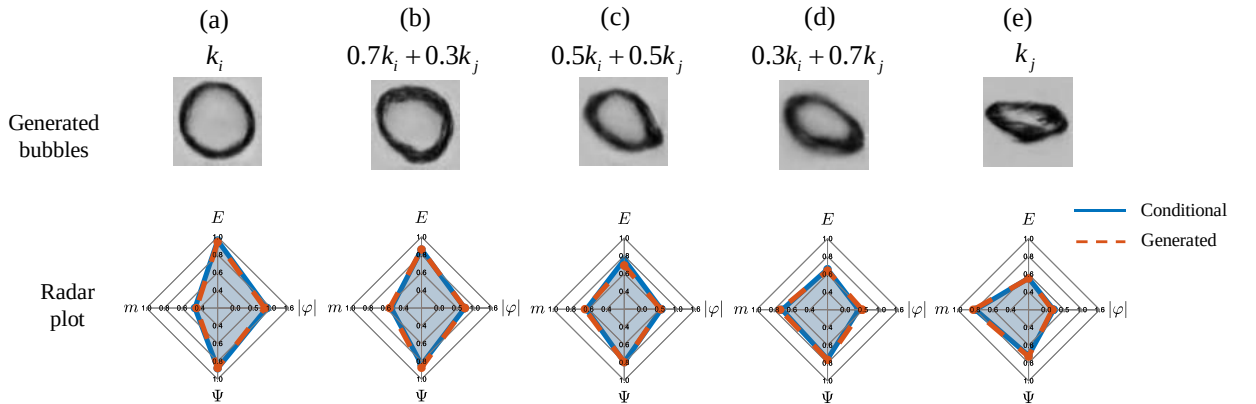


Fig. 5.10 Example of interpolating two bubble feature vectors k_i and k_j to generate bubbles outside the training dataset manifold. The five examples show the generated bubbles using the feature vector of (1) k_i , (2) $0.7k_i + 0.3k_j$, (3) $0.5k_i + 0.5k_j$, (4) $0.3k_i + 0.7k_j$ and (5) k_j .

5.3.2 Bubbly Flow Synthesis

To demonstrate the performance of the proposed BubGAN, a visual comparison of real and synthetic images are shown in Fig. 5.11 for typical bubbly flows. The real image captured by high speed camera is shown in Fig. 5.11 (a). Fig. 5.11 (b) and (c) show synthetic images generated using the conventional CCA method and BubGAN, respectively. It can be seen that the synthetic image generated by the CCA method, as shown in Fig. 12 (b), shows a noticeable difference compared to the real image. All the bubbles in the figure share a similar appearance and they do not present shape and surface distortions as appeared in the real image. The synthetic image generated by the BubGAN, as shown in Fig. 5.11 (c), shows a significant improvement in both shape variations and visual appearances. In the following, more examples are given by generating bubbly flow images in different flow channels.

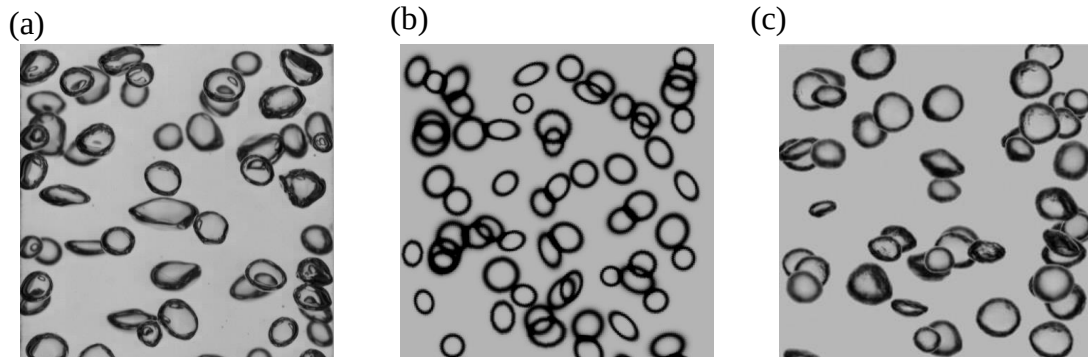


Fig. 5.11 Comparison of (a) the real bubbly flow images with the synthetic bubbly flow images generated based on (b) CCA model and (c) the BubGAN algorithm.

5.3.2.1 30 mm × 10 mm Rectangular Channel

For the rectangular channel with a cross section of 30 mm × 10 mm, air and water are injected uniformly at the inlet with the two-phase injector. Four test conditions are shown in Fig. 5.12. all with a superficial gas velocity fixed at $j_g = 0.1$ m/s. The superficial liquid velocity for Run 1-4 are $j_f = 0.5$ m/s, 1.0 m/s, 1.28 m/s and 2.12 m/s, respectively. High speed images are recorded at 1000 frames per second with a resolution of around 25 pixels per mm. The gas phase void fraction decreases with superficial liquid velocity j_f as j_g is a constant, whereas turbulence intensity increases with the increase of j_f . Under these varying void fraction and turbulence conditions, bubble size and number density decrease from Run 1 to Run 4. As can be seen in Fig. 5.12, images

generated by BubGAN can faithfully reflect the trends of bubble size and number density changes. The bubble shape is not limited to circular or elliptical shapes as compared to the CCA method.

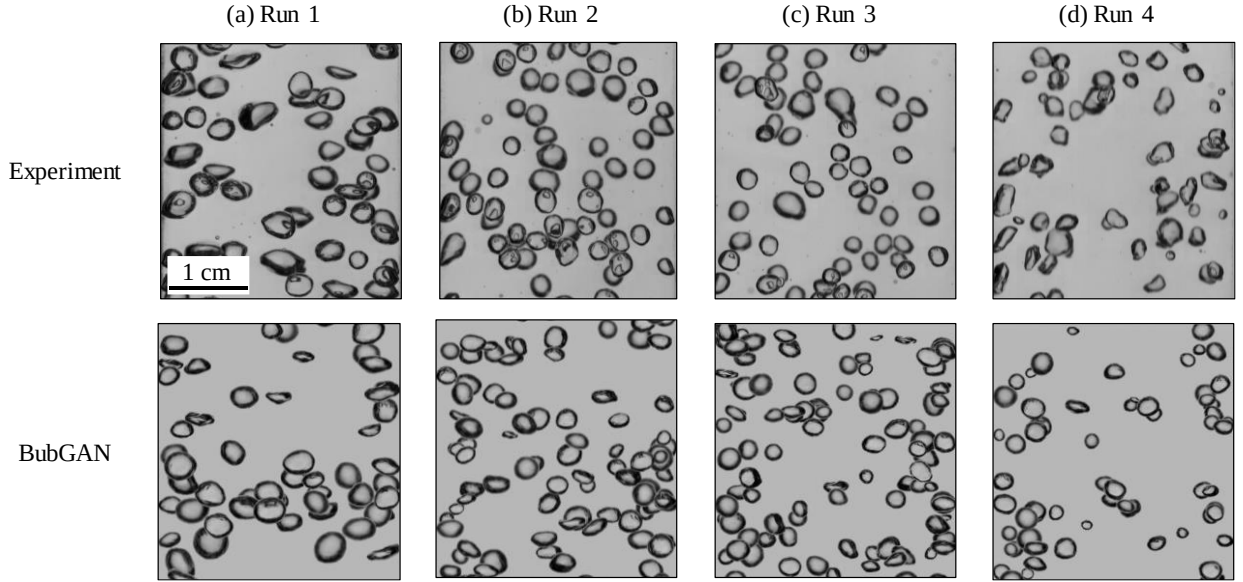


Fig. 5.12 Comparison of the experiment images and the synthetic images generated by BubGAN the 30 mm $\times$ 10 mm rectangular test section. The comparison includes the flow conditions of (a) $j_f = 0.5$ m/s, $j_g = 0.1$ m/s, (b) $j_f = 1.0$ m/s, $j_g = 0.1$ m/s, (c) $j_f = 1.28$ m/s, $j_g = 0.1$ m/s, (d) $j_f = 2.12$ m/s, $j_g = 0.1$ m/s.

5.3.2.2 200 mm $\times$ 10 mm Rectangular Test Section

Another example of synthetic bubbly flow image is given for a rectangular test loop with a cross section size of 200 mm $\times$ 10 mm. The test section has the ability to control the gas flow rate along the 200 mm width direction to form non-uniform bubble distributions. More details of the test facility can be found in previous works [86,87].

In this test channel, three gas injection modes are shown in Fig. 5.13. The experimental images are recorded at the height of $z/D_h = 10$, where D_h is the hydraulic diameter which is 19.05 mm for the test channel. The recorded images have a resolution of 4.77 pixels per mm. In Fig. 5.13 (a), gas is injected from the center region of the flow channel. The bubbles are mainly concentrated in the center region, and no bubble exists in the regions near both side walls. In Fig. 5.13 (b), the double peak mode is formed by injecting gas near the left and right walls. The bubble

number density decreases when moving towards the center region. In the third example as shown in Fig. 5.13 (c), the gas is injected near the left wall to form a single side peak pattern. As shown in the figure, the BubGAN can generate all three bubbly flow patterns accurately. The spatial distributions of bubbles in different inlet conditions are correctly reproduced in the synthetic images.

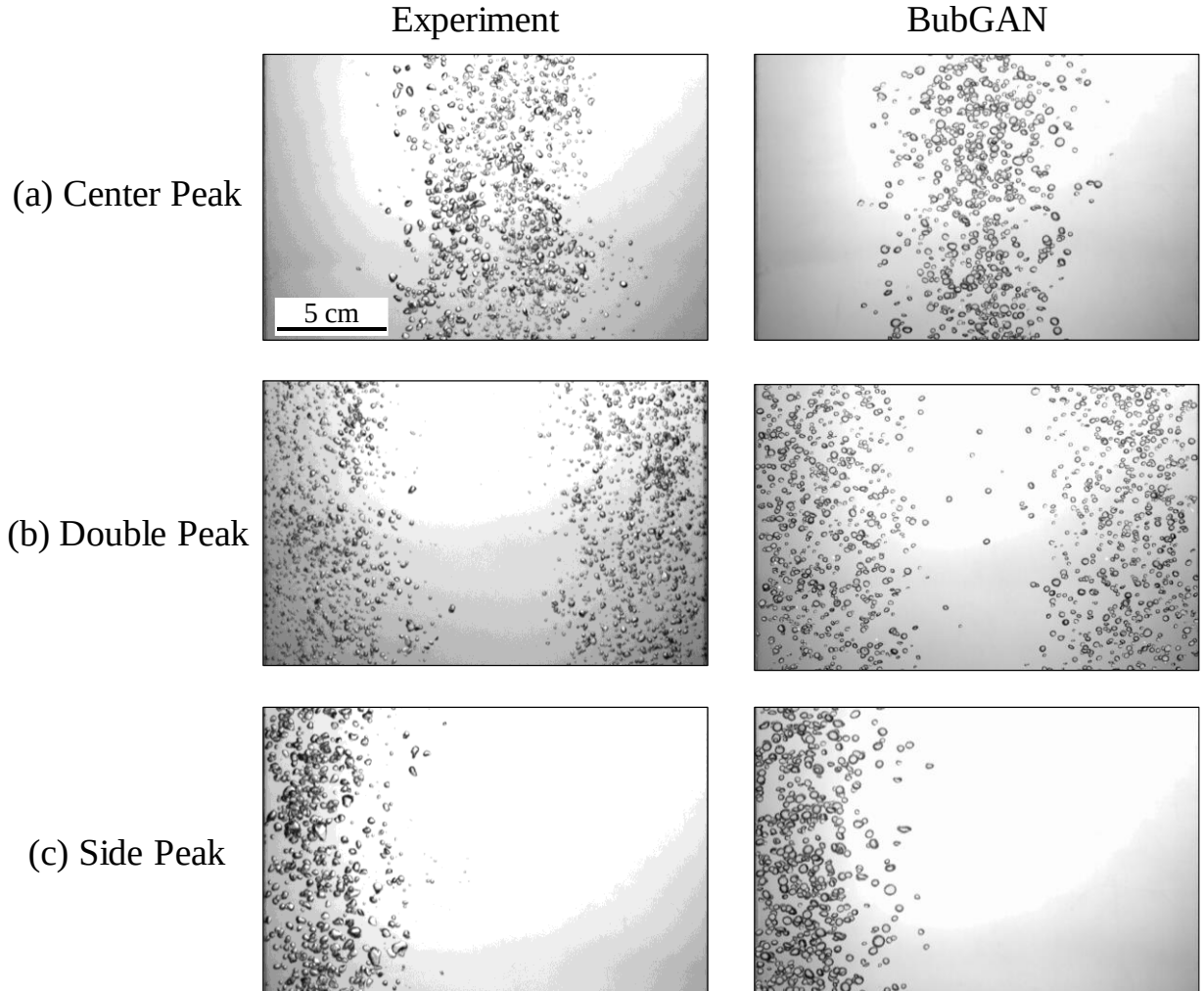


Fig. 5.13 Comparison of experimental images and synthetic images generated by BubGAN for the 200 mm $\times$ 10 mm rectangular test section. The generated images include three inlet bubble distributions (a) center peak, (b) double peak and (d) side peak.

5.3.3 Bubble Image Labeling

Detailed bubble label information is also available when synthetic images are generated using the BubGAN algorithm. Examples of bubble labeling are demonstrated in Fig. 5.14. The figure shows a synthetic bubbly flow image along with projection area, aspect ratio E and rotation angle φ labeled for each individual bubbles. Such information is automatically generated by the BubGAN algorithm without the need of any manual processing. These well-labeled images can be used to benchmark existing image processing algorithms [14, 17]. The red dots in Fig. 5.14 (b)-(d) represent the center of each bubble. This can be used to generate a bubble density map along with the synthetic bubble images. With this information, various machine learning algorithms [88–91] can be trained for bubble counting without additional cost for bubble labeling. The realistic images can also reduce the errors introduced by the discrepancy between synthetic and real images.

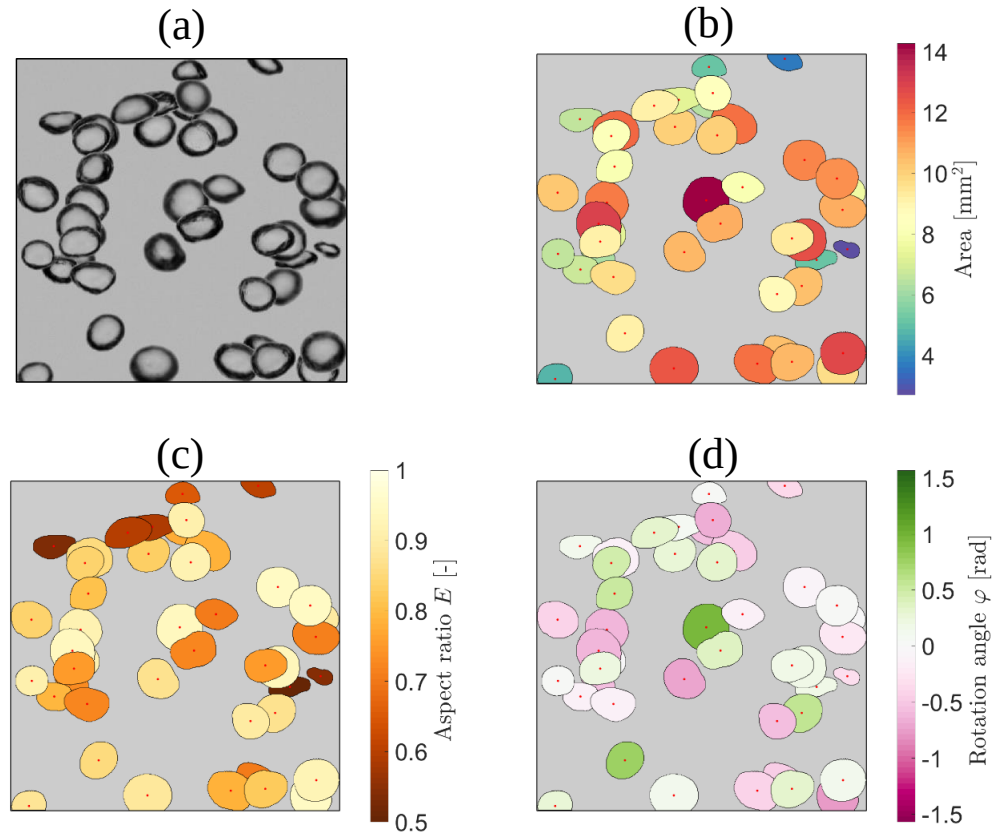


Fig. 5.14 Generation of a uniform distributed bubbly flow image with a million-bubble database with labeled bubble information, (a) synthetic image, (b) projection area, (c) aspect ratio and (d) rotation angle.

5.4 Summary

In this chapter, a BubGAN algorithm for bubbly flow image synthesis is proposed. The BubGAN combines image processing algorithms and the conditional-GAN to achieve automatic bubbly flow image generation and labeling. The generated bubbly flow images show a significant improvement compared to the conventional bubble models. This can help to assess the accuracy of existing image processing algorithms and to guide future algorithm development. The deep learning based object counting algorithms can also benefit from the BubGAN by greatly reducing the labeling cost. Four bubble feature parameters, namely, rotation angle, aspect ratio, edge ratio and circularity are integrated into the BubGAN algorithm. Therefore, one can generate a wide range of bubbles with desired bubble features. The quantitative assessments in Fig. 5.7 and Fig. 5.8 demonstrate the reliability and accuracy of the BubGAN in generating bubbles with given parameters. A tool for bubbly flow image generation is also developed based on a million-bubble database pre-generated by the BubGAN. The tool is capable of generating spatially uniform, as well as non-uniform bubbly flow images with detailed labeling information. Therefore, algorithm benchmarking and related deep learning algorithm training can be carried out without the additional cost of labeling.

6 Conclusion and Recommendations

This dissertation presents a comprehensive set of image processing algorithms for high-resolution bubbly flow measurement. The developed 2D image processing algorithm is the fundamental tool for processing the raw images recorded by either single or multiple high speed camera imaging systems. The accurate 3D bubble surface reconstruction is achieved with the proposed 3D image system and space carving method. The bubbly flow characteristics and bubble dynamic behaviors are studied with the proposed methods. A new synthetic bubbly flow generation algorithm (BubGAN) is developed to bridge the gap between the synthetic and experimental images, which can be used for algorithm training and benchmarking. The conclusions and recommendations are summarized as follows:

1. A robust 2D image processing algorithm is developed for bubble segmentation and outline reconstruction. The algorithm combined geometrical, optical and topological information in high speed images to achieve high accuracy in the image processing. The proposed algorithm has the capability of processing bubbly flow images with void fraction up to 17% in the 30 mm $\times$ 10 mm rectangular channel.
2. The uncertainty of the 2D image processing algorithm depends on the acquired parameter. For bubble number density, the error mainly exists in the segmentation of overlapped bubbles. For void fraction and interfacial area concentration measurement, it could be more complicated. Along with segmentation, estimation of bubble volume and surface area from 2D outline can be another influencing factor. The correlation between the third dimension along the camera axis and the bubble outline should be treated carefully to yield an accurate measurement.
3. Eight bubbly flow runs are studied in this work with various superficial liquid and gas velocities. The axial and transverse distributions of bubbly flow parameters are presented in this study. The acquired parameters include void fraction, interfacial area concentration, velocity, superficial gas velocity, Sauter mean diameter and bubble number density. The lift force effect was observed in several test runs, which formed a wall peak in the transverse void fraction profile by driving bubbles to near wall regions. The interfacial area transport equation shows a more complicated behavior in the axial direction. The pressure drop is the main factor for void fraction change, while the interfacial area

concentration can be affected by the different bubble breakup and coalescence mechanisms.

4. The IATE and bubble number density transport equation are benchmarked with the experimental data acquired in this 30 mm x 10 mm test facility. The results show that the IATE has an accurate prediction for the interfacial area concentration change along the axial direction. The number density transport equation prediction shows a discrepancy with the experimental data. This indicates that the empirical coefficients in IATE may not be used directly for bubble number density transport equation without further optimization.
5. A space carving method is developed for 3D bubble reconstruction with a four high speed camera imaging system. The proposed method is flexible with the number of high speed cameras used for experiments. More cameras can usually yield a more accurate measurement. The experimental test shows that the four camera imaging system can measure bubble volume with an error of less than 2% compared to the syringe reading.
6. The four camera imaging system is used to benchmark the uncertainties existed in single or two camera systems. The two-camera system has an error around 10% and the single camera system can have an error of more than 25% depending on flow conditions and test facility geometry. In scenarios where optical access is limited, the single or two-camera systems may still achieve reasonable results with proper assumptions for reconstruction.
7. The 3D imaging system proposed in this dissertation is proved to be more suitable for bubble rotation and aspect ratio measurement. The study shows the test channel wall can have a significant influence on the bubble rotation and aspect ratio value, especially when the bubble is close to the wall. The study shows that the aspect ratio correlation developed with one or two-camera systems can have an overestimation compared to the results acquired from the current 3D imaging system.
8. The 3D reconstruction algorithm is currently tested only for a series of single bubbles in stagnant water. Further study of bubble behaviors in a bubbly flow or bubble swarms can be carried out in the further study with the 3D imaging system. In this way, the 3D bubbly flow distribution along with individual bubble state can be acquired instantaneously in the measurement. This will provide useful data for benchmarking the 3D Multiphase Computational Fluid Dynamics (MCFD) codes.

9. In terms of 2D image processing algorithm benchmarking, the conventional synthetic images are generated using simple mathematical bubble models. These models generally assume the bubble intensity distribution in the images follows a concentric circular/elliptical arrangements (CCA). The generated bubbly flow images still have a large gap compared to the real bubbly flow images. The proposed BubGAN is a framework to address this problem by generating more realistic bubbly flow images.
10. More works need to be done for assessing the image processing algorithms by using the synthetic images generated from BubGAN. In this way, the uncertainties from the algorithm can be better understood and the accuracy benchmarked with the realistic synthetic images would be closer to the real performance in processing experimental images.
11. The framework proposed in BubGAN can be extended to generate different flow regimes in two-phase flow. A Two-phase GAN will be developed for generating realistic two-phase flow images in the future. This can help to advance the development and application of image processing techniques in the full spectrum of two-phase flow regimes.

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