Detection and Tracking of Bubbles in Two Phase Flow

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Declaration

I, *Altaf ur Rahman* declare that this thesis titled "Detection and Tracking of Bubbles in Two Phase Flow" and the work presented in it are my own and has been generated by me as a result of my own original research.
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This thesis is dedicated to *my beloved parents, wife and my children*

Abstract

Bubble detection and tracking is an important and complex part of motion analysis of two phase air-water flow in non linear wavy channels in which bubble speed and size varies and sometimes bubble occludes with the boundaries of the other bubbles. Due to optical noise bubbles boundaries are not recorded completely in a camera and then need to be filled intelligently to recognize them as single entity in a non-convergent sinusoidal channel. To solve this problem non linear sinusoidal curved channel is transformed to a linear straightened horizontal channel and then trail and error method of segmented morphological operations are applied to identify each bubble as a single entity and should not be occluded with the other bubbles. The detected bubbles are associated across different frames based on motion, estimated by Kalman filter to predict frame by frame detections and the likelihood of every detections assigned to each track. Since a Kalman filter is a good estimator for linear motion so path based approach to the sinusoidal channel is more robust, as it linearizes the motion of the sinusoidal channel to study a non linear motion model. Finally the result shown that our path based straightened channel gives more accurate results for both bubble count and computational velocities than non-convergent sinusoidal channel.

Keywords: *Bubbles, Bubble Detection, Bubble Tracking, Kalman Filter, Non Convergent Sinusoidal Channel*

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Contents

1 Introduction 1

1.1 Machine vision in two phase flow 2

1.1.1 Number of bubbles 3

1.1.2 Bubbles velocities 4

1.2 Applications 5

2 Literature review 6

2.1 Bubbles in two phase flow 6

2.1.1 Related work 6

2.2 The problem 10

3 Methodology 12

3.1 Experimental setup 13

3.2 Computational methodology 13

3.2.1 Pre processing 13

3.2.2 Post processing 16

3.3 Methodology steps 19

4 Results and discussion 21

4.1 Measuring number of bubbles 21

4.2 Measuring velocity 23
4.3 Discussion 24

5 Conclusion **29**

References **31**

List of Figures

1.1 Path based approach to sinusoidal channel 4

3.1 Experimental setup 14

3.2 Two- phase flow air and water channels (complemented image) . . . 15

3.3 Methodology of the whole process 18

3.4 Morphological operations applied in sinusoidal channel 18

3.5 Morphological operations applied in path based approach to sinusoidal channel 19

4.1 Different flow samples tracking in both path based and sinusoidal channel 22

4.2 Comparing results of tracking for bubble count 23

4.3 Velocities comparison for both sinusoidal and path based approach . 24

4.4 Kalman based motion estimation in our path based linear channel . 25

4.5 Kalman based motion estimation in sinusoidal Channel 27

4.6 Percentage error in velocity calculation 28

4.7 Percentage error in calculating bubbles count 28

List of Abbreviations and Symbols

Abbreviations

Q_i	Volume flow rate (mm^3/sec)
v_i	Velocity of two phase flow (mm/sec)
v_{iE}	Experimental velocity (mm/sec)
v_{iC}	Computational velocity $pixels/frame$
A	Area of the channel
n_h	Height of the channel
n_w	Width of the channel
S_i	i^{th} video Sample
p_m	No of pixels per mm
f_i	I^{th} frame
I_o	Sinusoidal Channel image
I_r	Recovered sinusoidal channel image
ROI	Region of interest

x	State of a bubble
p_i	Position of a bubble in f_i
v_i	Velocity of a bubble in f_i
Δt	Change in time
$\mathbf{x}_i$	State estimation at f_i
$\mathbf{C}_i$	Estimation of covariance matrix at f_i
P_i	Prediction matrix at f_i
$\mathbf{N}_i$	Control matrix of external influence at f_i
u_i	External uncertainties
$\mathbf{M}_i$	Additional environment uncertainty
$\mathbf{L}_i$	Difference matrix between measured and predicted state units
m_k	Observed readings
$\mathbf{K}$	Kalman gain
x'_i	New Kalman filter State
$\mathbf{C}'_i$	New covariance matrix
$\mathbf{K}'$	New Kalman Gain

Chapter 1

Introduction

Multiphase flow is an important topic in fluid Dynamics. It is an enormous and growing field and has a large diversity of flow forms.This makes necessity of fundamental research to better understand the physical science both for numerical and theoretical work on controlled experiments. One of the fundamental type of multiphase flow is gas liquid two-phase flow which have different flow characteristics, different behaviors and flow patterns. Two phase flow can be separated and dispersed gas liquid flow where one fluid is present in droplet , particles or in the form of bubbles. Categorization of accepted method is the consideration of velocity of each phase in two phase flow.

Machine vision is an important and convenient tool technically studying behavior of two phase flow. In two phase flow two fluids such as gas and liquid are flowing through any channel of any cross sectional area. The total mass transfer of gas in the liquid is characterized by many parameters like number of bubbles, bubble size, bubbles size distribution and bubble dynamics. Identifying the accurate volume of gas transfer depends on the correct number of bubbles to be detected by the vision system. The volumetric flow rate is proportional to the cross sectional area of the channel and velocity of fluid in the channel. This volumetric flow measured in some length units like mm/sec can be also studied in imaging system by measuring bubbles position change in image pixel coordinates with the units of $pixels/frame$.

Motion estimation through non convergent serpentine sinusoidal channel is a non linear task and it is difficult to morph region in sinusoidal channel with the simple morphological operations. Also, Kalman filter has poor performance to track entities in a curve path. To solve this problem we solved the problem with the path based approach by transforming the whole motion in to a straightened horizontal channel , a linear model of the curved channel to study the non linear motion.

Now digital Imaging of two phase flow results in Images included optical noise. Illumination condition causes contrast reversal and multiple inter-reflections. This results in recording of some extra noise and channel boundaries with bubbles which causes occlusion. This problem is solved through segmented morphology to remove noise in an efficient way and doing correct blob analysis to detect bubbles in two phase flow. Both sinusoidal channel and our path based approach were tracked through a Kalman filter and results are far good for path based approach both in counting number of bubbles and calculating flow velocity.

1.1 Machine vision in two phase flow

Nowadays high speed imaging is very important to studying and understanding the science of very fast occurring phenomena such as studying fast and non linear motion. Accurate mass dispersion and mass transfer of gas in to liquid has many important applications and studying it with naked eye or other conventional equipment have a lot of limitations. Machine vision at this stage is matured too much and very intelligent with its huge development in image processing and computer vision based techniques and equipped with very high sensitive cameras of thousand frames per second to understand the phenomena of gas-liquid two phase flow.

Main factors of consideration in the motion analysis of machine vision is to develop a good experimental setup. Main parts of a machine vision systems are a camera, scene of the two phase flow and a good illuminating conditions. High speed imaging sensors should be primarily part to capture the total science of motion. Also the illuminating conditions should be better to capture the bubble size and perimeter accurately. since bubbles are transparent in nature ,we get two problems due to illuminating conditions contrast reversal and multiple interreflections. Shadows are formed every where and when image is complemented on its intensity values it is shown that there is information of shadows occluded with the bubbles data. when light pass from one medium to another medium it causes interreflections and series of these interreflection induces noises in the recording of two phase flow.

The total mass transfer of gas in gas liquid two phase flow is parametrized by amount of gas flowing such as number of gas bubbles, bubbles size, bubbles size distribution, flow dynamics etc. We here worked on calculation of number of bubbles and velocity of the air bubbles in air water two phase flow.

1.1.1 Number of bubbles

In two phase flow it is important to calculate the accurate number of bubbles for motion analysis of two phase flow. Bubble release equipment releases different types of bubbles depends on different mechanical parameters produce different behaviors of bubble-bubble, and bubble-boundary interactions. This has effect on the shapes of the bubbles in gas-liquid two phase flow. Bubbles also occlude, merging and breaking up with other bubbles makes it difficult for identifying by the machine vision algorithms. The flow behavior of the Sinusoidal channel is non linear and tracking them is quite difficult task. Tracking and motion estimation by Kalman filter is based on Kinematics equation and any occlusion of bubbles makes the motion estimation along the wrong path. So for this reason the non convergent serpentine sinusoidal channel has been solved by a path based approach which makes the channel linear and a non linear motion is studied into a linear pattern which is more accurate to count the number of bubbles in the Sinusoidal channel.

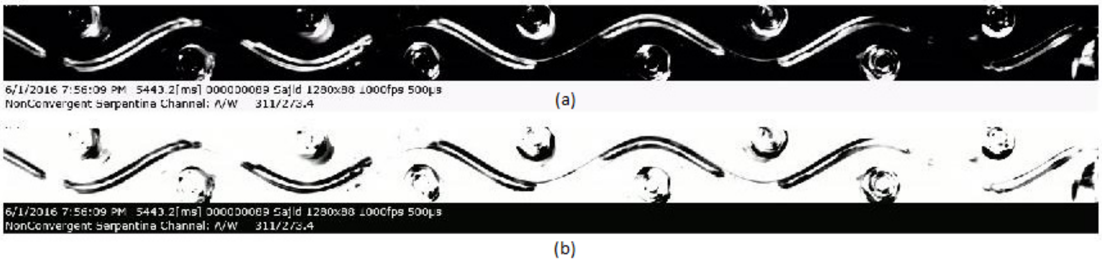

Figure 1.1: Path based approach to sinusoidal channel

(a) Original image recorded of the air-water two phase flow (b) Complemented Image

1.1.2 Bubbles velocities

In a Machine vision system, velocity of the bubbles is computationally measured in terms of how much the bubbles have advanced per frame ($pixelsperframe$). This is very accurate and reliable technique to measure velocities without need of velocities measuring mechanical instruments. So with the use of single camera it is make possible to measure too much parameters however it should be properly calibrated and the more high imaging sensor the more we are able to calculate the velocity better. We have shown in the result section that our approach to the Sinusoidal curved channel have better estimation than sinusoidal curved channel.

The structure of this thesis is divided as,

In chapter 2 related work related to two phase flow is presented. First the bubble behavior in linear and non linear wavy channels is discussed followed by analysis of imaging techniques are brought under consideration. Different bubble detection techniques such as geometric and appearches approaches with other techniques are discussed. Finally the problem is formulated for simple blob analysis in path based approach and kalman filter is discussed for tracking the motion of two phase flow.

In chapter 3 the methodology of experimental setup for imaging and the computational methodology are mentioned. Images were taken through high imaging sensor and processed in system specification given. The pre-processing of samples for detection with segmented morphological operations are technically applied through step by step. At the end post processing operations with detection through blob analysis and tracking through the linear Kalman filter are evaluated.

Chapter 4 discusses results both for sinusoidal and path based approached channel. Technical discussion was made due to optimal results of our linear approach in morphological operations and tracking results. Different graphs for bubble count and velocities , with other handfull figures are presented to clear out the techs in the imaging of two phase flow.

Chapter 5 finally concludes machines vision importance for two phase flow and how path based approached has contributed better in calculating the benchmark bubble parameters i.e, bubble count and bubble velocity.

1.2 Applications

Two phase implies in many case studies like large scale power systems. Large boilers are used in coal and gas fired power stations to produce steam for turbines, and so for designing boilers a through understanding of two phase flow is necessary. Similarly to remove heat from nuclear reactors water is used using two phase flow. There are great studies to understand the design of pipework to avoid possible failures, loss of pressure and many more. Similarly the study extends to pump cavitation, marine propellers where a change in pressure can cause a phase change in the two phase flow. the collapse of the vapor bubble can produce pressure spikes can damage the propeller or turbine overtime. A vision system can detect such collapse and can be studied more accurately these fast occurring phenomena.

Air and water is one form of two phase flow further mainly to understand the multiphase flow in different process. In many engineering fields multiphase flow studies can be found. such as aerospace, chemical, electrical, environmental, mechanical, bio medical and nuclear engineering. so it has variety of applications for example rocket engines, nuclear and chemical reactors, contamination spreading, transportation of multiphase mixture, cavitation, ink-jet printing, cooling of multiphase flow, gases drying etc.

Chapter 2

Literature review

2.1 Bubbles in two phase flow

Bubble flow in multiphase flow is an important research topic due to its wide and large numerous applications in different processes and effects in different equipment. The extraordinary work done reviewing the bubble flow in multiphase flow specifically in two phase flow system by Hassan Abdulmouti [1, 2] is 133 page long defines the bubble flow characteristics, behavior, structures and two phase flow patterns along with its parameters in different two phase flow processes.

2.1.1 Related work

Machine vision of mass dispersion, mass and heat transfer of gas-liquid is important in many applications such as detection of air bubbles in dense dispersion [3] and air bubble segmentation in multiphase flow [4]. This motion analysis of bubbles is characterized by many bubble parameters . The correct identification of gas volume through machine vision can lead to an accurate assessment of film mass transfer coefficient [5] [6]. Furthermore, if the intrinsic reaction kinetics are known in a multiphase flow problem than the rate of reaction can be determined from the dynamics of the gaseous phase in the liquid [7].

Digital image processing is a convenient and efficient tool in measuring bubble parameters like volume, size and size distribution, number of bubbles and bubble velocity. Junker [8] has reviewed in detail the analysis of machine vision systems in bubble analysis with a detailed summary of experimental techniques using different image sensors and its specifications. Some of the devices studied for bubble machine vision system are CCD(charge couple device) manufactured by different industries with various specifications such as Sony, Sanyo and Hitachi. These high speed vision sensors with thousand frames per second for studying bubble flow in two phase flow depends on flow behavior with merging and bubbles breakup causes occlusion betweeen bubbles, was divided into segmentation and bubble reconstruction approaches by [9–11] . Bubble detection techniques were further reviewed by [12] separating the detection as geometric and appearance based approaches.

Geometric approaches

In geometric approaches geometric properties of object accounts for identification.Every geometrical shape has its own properties. For example for circles identification, its centre, radius, arcs , position coordinates and for ellipses detection radius, major and minor axis, spatial or radial coodinates, area are some geometric factors of identification. To detect geometrical models a regular bubble shape models such as circular and elliptical are fitted on an image map and those geometrical shapes are identified despite they have different sizes and rotations. Richard O duda [13] has used Hough transform (HT) for identification of lines based on simplyfying computation with angle radius despite the parameters of slope intercept. A circle can be defined by the circle equation

$$(x-g)^2 + (y-h)^2 = r^2$$

where (g, h) are circle coordinates and r is radius of the circle. An orbitrary coordinate point (x,y) is transformed into right circullar shape (g,h,r) in the space of parameters. The intersection will be on a single point if the image points completely lies on a circle will output the coodinate of the centre point and the radius of the cirlce. The different version of HT for circles detection approached with modifiend methods is reviewed by [14]. A genetic algorithm for circle selection

[15] based on chromosomes three edge points (g,h,r) encoding and then the result of the fitness function tells about the circles detection. A semi automatic bubbles reconstruction using improved version of Hough Transform was presented by [16] with manual removal of false positives.

Hough transform methods suffers from computational complexity and requires higher storage space so other geometric approaches like stochastic and evolutionary based methods are present in literature for minimzing the computational complexity and storage requirements. Similarly gradient information based approaches were devised by [17] with probabilistic pair wise voting technique using Hough transform extention for circular object detection by formulating detection as intersection of lines in the paramteric space which is three dimensional.

Geometric techniques such as hough transform based detection methods have various application such as spherical particles segmentation in image stacks with transmitted lights [18] , bioreactors complex dispersions for segmentation of bubbles and drops [16] and medical imaging analysis in medical vidoes for circular objects detection [18].

Appearance based approaches

These approaches depends on the appearance of bubbles with different regular or irregular shapes and has optimal results if correct measures are taken into account. Here a bubble with some predefined template in a template database is convolved with the bubbles and the result is local maxima of the convolution [19]. Database should have all templates of bubbles which depends on the behavior of two phase flow. Linear or non linear two flow in horizontal or vertical columns, wavy channels having different flow conditions and having bubble to bubble and bubble to boundary interactions can have effect on the shape of the bubble and they can change when move from one place to another. Also the experimental setup with illumination conditions have effect on the bubbles boundaries recorded as close countours or incomplete bubble perimeter also with addition of channel noise. convolution is a technique to find similarity between two signals, the point at which two signal have same phase results in local maxima. This convolution helps in finding the match between the bubble template data base and the original online experimental imaging or videos samples. The technique is based on sliding window to detect the bubbles with the given approach.

An illumination correction technique based on appearance approaches for the performance of bubble detection was presented in [20] enhances the contrast in several steps where every step was pre filtered for removal of unimportant information from the image.A multiple scaling Template matching algorithm [3] is presented with the image convolution. Here multiple bubble prototypes such as bubbles rotation with different bubble templates. The method is optimal than Hough transform but the computational complexity is a problem for this approach. A rain drop appearance based technique [21] with saliency maps of color and texture raindrop candidates were detected through its shape based features

Other approaches

Other approaches of bubble detection which share the same characteristics with biological cell segmentation are region growing, morphological operations and feature detection. A difference matric exists between bubble identification and biological cells segmentation, as bubbles have interactions with themselves and with boundaries exerts different forces changes the shapes of the bubbles. Moreover bubbles shapes mainly depend on the channel [22] changes the bubble to an irregular shape. Detection of objects through Blob analysis [23] is an efficient and simple method to identify connected pixels but it needs to fill the bubbles intelligently and remove the optical noise requires good experimental setup for accurate imaging with illumination correction. Optical noise can vary through overall image map can be solved by segmented the image and apply different morphological operations [24] to extract bubble information correctly. Segmented morphology has been applied in Underground pipes classification by images [25] and text line extraction from clutters and different orientations [26]. After bubble detection through blob analysis [27] they are associated frame by frame for tracking them in subsequent frames in a video. Kalman filter [28] further explained by [29] is an accurate tool to estimate linear motion of the bubbles in the subsequent frames with the kinematic model.

2.2 The problem

We studied from literature here the importance of bubble flow characterized by different flow parameters to study the gas liquid two phase flow behavior. However techniques presented in literature have both positive aspects and limitations. Geometric techniques based on geometrical information of bubbles fitted on overall Image map works better, when the bubble shapes are defined such as circles and elliptical objects with radius, angle, arcs, coordinates, major and minor axis etc, which are easy to define. Geometric techniques will fail for irregular shapes whose shapes are not defined clearly. Appearance based techniques are the convolution maxima of the template data base with the image bubble entities. Appearance based techniques suffer from computational complexity and large accurate database failing it will result in large false positives. Moreover both geometric and Appearance based techniques are mostly developed for vertical column with bubble having less contact with the boundary.

Non linear wavy channel such as sinusoidal makes the study of motion analysis more complex where bubbles shapes are irregular with elongated wavy bubbles and merging of bubbles due to compression forces caused by Dean vertices. This leads for accurate,fast and robust detection and tracking of bubbles in a non linear motion model for thorough understanding the science of two phase flow.

We approached the bubble detection problem with segmented morphology first to morph the bubbles as closed contours and then blob analysis to detect the connected number of pixels i.e, bubbles . Moreover we approached the Curved channel with the path based approach straightened horizontal channel to study the non linear motion in to linear model. Morphological operations in our straightened channel fills the bubbles accurately than sinusoidal channel.For bubbles tracking problem, since our path based approach is linear so it better estimates the motion through the linear Kalman filter than the non linear sinusoidal channel.

In this study the motion analysis of only two bubble parameters in two phase flow is considered which are number of bubbles and the bubble velocity.

Chapter 3

Methodology

Estimation of Bubble parameters such as number of bubbles and computational velocity calculations depends on the accurate detection and tracking of bubbles in two phase flow. Bubbles are not clearly defined in raw images directly from the camera.Bubbles are transparent and not recorded as a closed contour during imaging, many boundary pixels are not shown and it makes hard to identify the single bubbles. Also, the illumination conditions causes contrast reversal and multiple inter-reflections, this results as optical noise and many false pixels such as channel pixels are shown in the output of the imaging system. We solved here this problem with segmented morphology. Also the dynamic model of non convergent serpentine sinusoidal channel is non linear, we approached this model with a linear path based approach having the non linear motion characteristics. This has better result in segmented morphology and tracking the bubbles with the Kalman filter.

A non convergent serpentine sinusoidal channel having cross sectional area A in which air and water is flowing with a flow rate of Q_i and v_i as a velocity of two phase flow is,

$$Q_i = Av_i$$

A camera is installed to capture the 2D video of the fluid flow such that height of this sinusoidal channel can be given as n_h and width as n_w both measured in mm of the i^{th} sample video S_i. Experimentally velocity of i^{th} video samples can be given with a unit of mm/sec,

$$v_{iE} = Q_i/A \tag{3.0.1}$$

if p_m shows number of pixels per mm, so Computationally velocity v_iE can be represented in pixels per frame as,

$$v_{iC} = p_m v_{iE}/f_i \tag{3.0.2}$$

f_i is frame rate of sample video S_i.

3.1 Experimental setup

Fig 3.1 shows the experimental setup of the two phase flow. Water from a tank and air from the compressor are flowing through a pump with flow rates measured by a flow meter is mixed with air in the mixer. The entrance length to the sinusoidal chnnel is 50 mm to make the flow stable. Then the mixture of air-water i.e, two phase fluid is passed through a sinusoidal channel having 2mm x 4mm cross sectional area and length is 200mm long wavy portion. At outlet length is 10mm for steady flow exit from which fluid is flowing back to the water tank where bubbles escape, and the the flow is closed means the process is continuous. Images from the sinusoidal channel is acquired by a high speed imaging sensor Mikrotron MotionBlitz MC1370 camera at a frame rate of 1000 frames/sec. Vidoes samples were taken at different flow rates, bubble size, velocity to study the two phase flow in sinusoidal curve channel efficiently.

3.2 Computational methodology

3.2.1 Pre processing

Data directly from Camera are in the form of raw sequence of images which have variety of problems. One of the most common problem to be counted for solution is contrast reversal and multiple interreflections [30] termed as optical noise due to

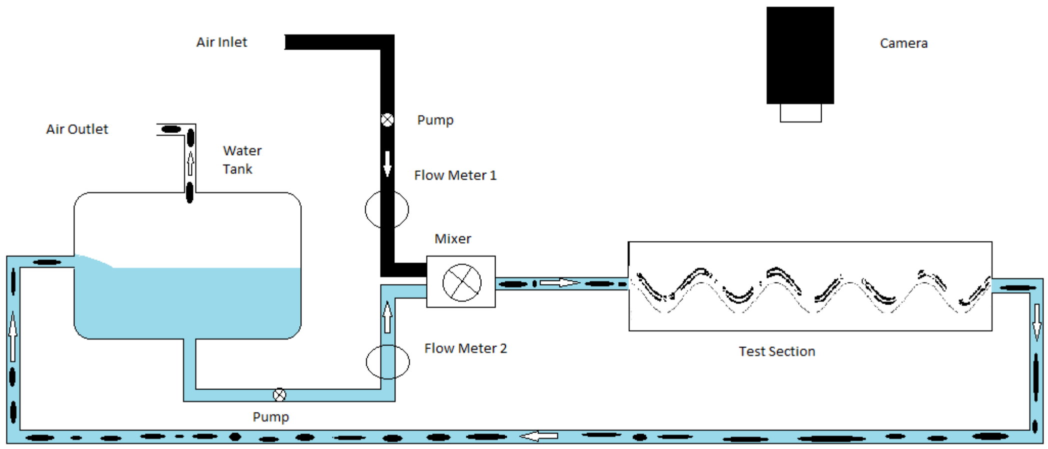

Figure 3.1: Experimental setup

illumination conditions while recording the video of the flow process. This optical noise causes bright ridge edges of the channel, irregular bubbles shape and poor boundary of bubbles vary in intensity at different segments of the image.

To remove optical noise and identifying the bubbles incomplete boundaries as bubbles contour, method of morphological segmentation is addressed [23]. Images from the particular sample is divided into different segments on the basis of different morphological operations for accurate identification of each bubble, its boundary and to remove the optical noise efficiently. Binary morphology is to use morphological operations on binary images converted from other color images like RGB or Grayscale with the a certain threshold prior to morphology [31]. Here we used four types of binary morphological operations.

Close operation is applied to close any bubble boundaries

Erosion to remove any optical noise induced randomly shaped and randomly distributed artifacts not belong to bubbles in the foreground segmented image.

Dilation to recover any original bubble pixels eroded due to process of erosion.

Different kernals of the above morphological operations were applied in every segmented area of the image for improved results. This morphological segmentation is a complex task and based on trail and error method to acquire the desired results. For better results of morphological segmentation and accurate bubble tracking

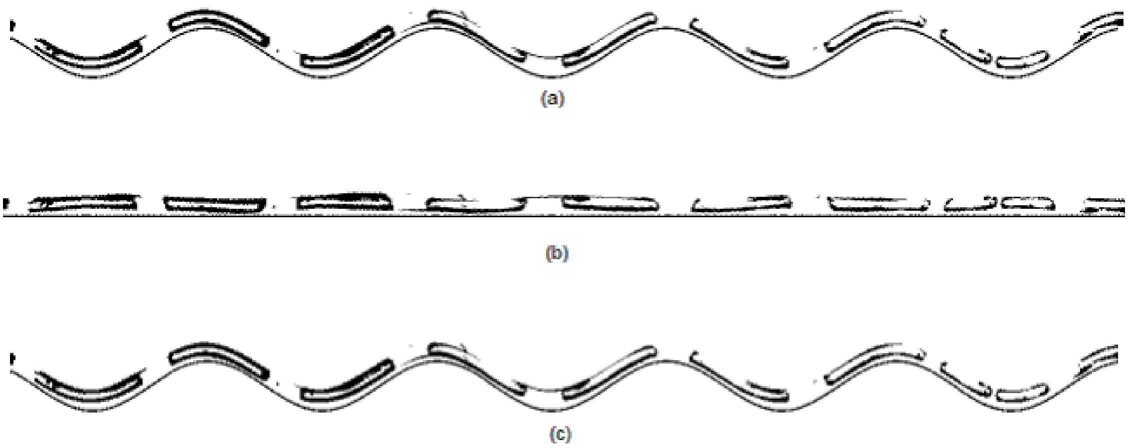

Figure 3.2: Two- phase flow air and water channels (complemented image) (a) Original sinusoidal channel (b) Path based approach to original sinusoidal channel (c) Recovered sinusoidal channel from path based straightened channel

original non serpentine sinusoidal channel was transformed to a straightened horizontal channel called as path based approach. This transformation can be given as,

For very first pixel of the channel in the first column,

$$\sum_{i=0}^{i=no\,of\,columns} \sum_{j=0}^{j=no\,of\,rows} P_i = R \tag{3.2.1}$$

Equation 3.2.1 shows that very first pixel of the channel is moved to the reference row R. Then all other pixel in the particular row are copied in the same order to the reference row and the whole process is repeated for every column, so all sinusoidal channel pixels will copied to a reference row which we call it our approach of straightened channel. Percentage error while recovering the original sinusoidal channel from the path based channel is,

$$E = \frac{I_o - I_r}{I_o} 100 \tag{3.2.2}$$

I_o is original sinusoidal curve channel and I_r is recovered sinusoidal channel back from straight channel.Experimentally percentage error was $\sim 1 - 2\%$ pixels.

3.2.2 Post processing

Bubble detection Region of interest (ROI) i.e, Area of the channel has been extracted from the Original video then segmented morphological operations were applied discussed in last section followed by blob analysis to detect each connected number of pixels i.e, bubbles.

Bubbles association Association of bubbles in each frame f_i with f_{i+1} is associated based on estimation of kinematic motion model. Every bubble has its own position and its velocity i.e, state in each frame. To predict the next state of each bubble in next frame is estimated through a Kalman filter, which only counts the previous state parameters and predict the new state. We present here the model of Kalman filter to track the bubbles. A State of each bubble is given by its position and velocity,

$$\mathbf{x} = [p \quad v]^t$$

Let the position and velocity of bubble in frame f_i is,

$$p_i = p_{i-1} + v_{i-1}\Delta t + 1/2at^2 \tag{3.2.3}$$

$$v_i = v_{i-1} + a\Delta t \tag{3.2.4}$$

Where p_i is the new position, p_{i-1} is the current position, Δt is the change in time , v_{i-1} is current velocity and v_i is the new velocity at f_i. Or matrix form of the next state of the bubble,

$$\mathbf{x}_i = \mathbf{P}_i\mathbf{x}_{i-1} + \mathbf{N}_i u_i \tag{3.2.5}$$

$$\mathbf{C}_i = \mathbf{P}_i\mathbf{C}_{i-1}\mathbf{P}_i^T + \mathbf{M_i} \tag{3.2.6}$$

Equations 3.2.5 and 3.2.6 represent estimated values for both position and covariance matrix, here covariance gives us the correlation between position and velocity. Where $\mathbf{x}_i$ and $\mathbf{C}_i$ are new estimate of position and Covariance Matrix , P_i is the prediction matrix, x_i and $\mathbf{C}_{i-1}$ are current best estimates, $\mathbf{N}_i$ is the control matrix of any external influence , u_i are any external uncertainties and $\mathbf{M}_i$ are any additional environmental uncertainty.

Now measuring the state variables of bubbles may have an uncertainties, and we need to incorporate those uncertain values in our Kalman filter to track the bubbles efficiently. There can be a difference of units between the measured values and the tracking state so this difference is captured in another matrix $\mathbf{L}_i$. Combining these predicted state and the measured state will result in new equations,

$$\mathbf{x}'_i = \mathbf{x}_i + \mathbf{K}'(m_k - \mathbf{L}_i\mathbf{x}_i) \tag{3.2.7}$$

$$\mathbf{C}'_i = \mathbf{C}_i - \mathbf{K}'\mathbf{L}_i\mathbf{C}_i \tag{3.2.8}$$

$$\mathbf{K}' = \mathbf{C}_i\mathbf{L}_i^T(\mathbf{L}_i\mathbf{C}_i\mathbf{L}_i^T + \mathbf{U}_i)^{-1} \tag{3.2.9}$$

Equations 3.2.7, 3.2.8 and 3.2.9 are the correction steps of Kalman filter counting the covariance of the uncertainty $\mathbf{U}_k$ and m_k is the mean of distribution or the observed reading. x'_i , $\mathbf{C}'_i$ and $\mathbf{K}'$ are new Kalman based best estimation for state, covariance matrix and Kalman gain respectively. The original Kalman gain is given by,

$$\mathbf{K} = \mathbf{L}_i\mathbf{C}_i\mathbf{L}_i^T(\mathbf{L}_i\mathbf{C}_i\mathbf{L}_i^T + \mathbf{U}_i)^{-1} \tag{3.2.10}$$

Using equation 3.2.7 the state of the bubbles that is its position and velocity can be determined.

Fig 3.4 and 3.5 shows output of morphological operations to identify bubbles both in sinusoidal channel and path based approach to sinusoidal channel. The image is taken from the same sample with the bubble red circled bubble cannot be connected either in x or y coordinates in sinusoidal channel but it can be easily filled with morphological operations to connect x-axis as single bubble in the straightened channel due to path based approach

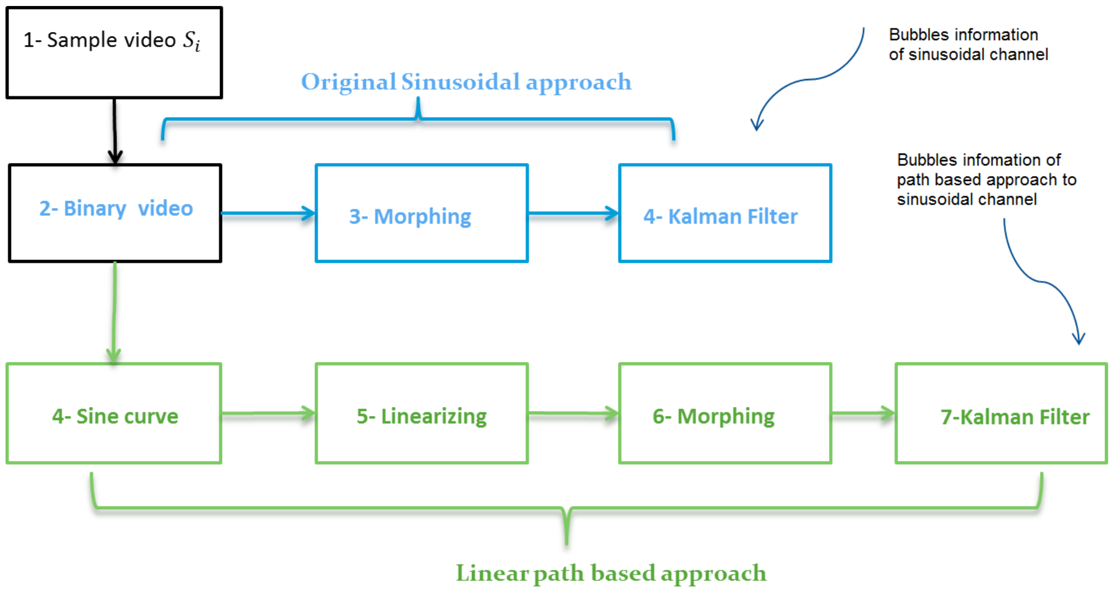

Figure 3.3: Methodology of the whole process

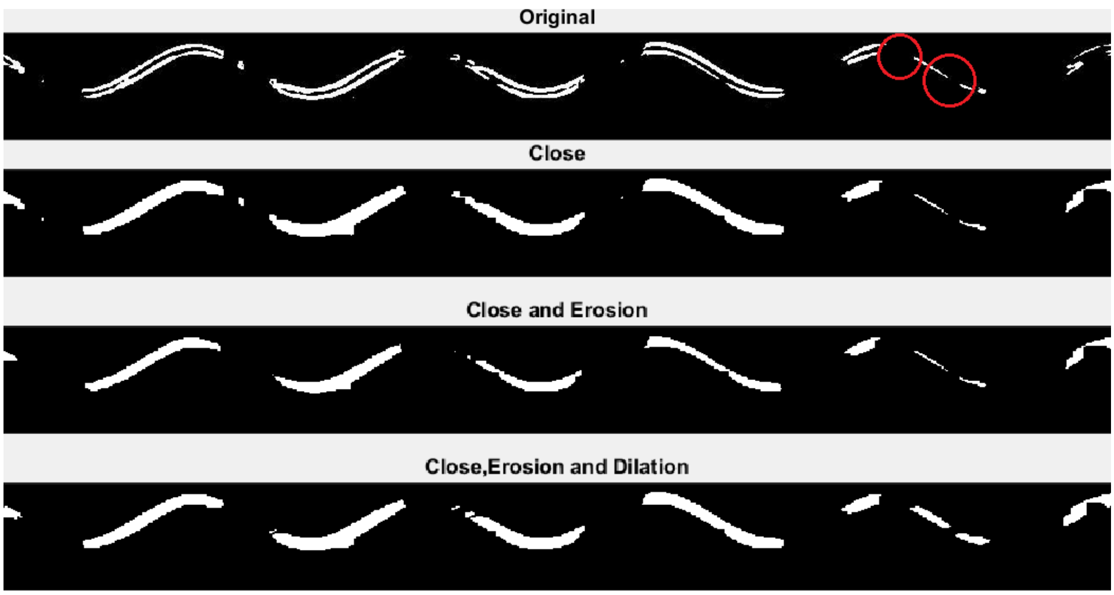

Figure 3.4: Morphological operations applied in sinusoidal channel

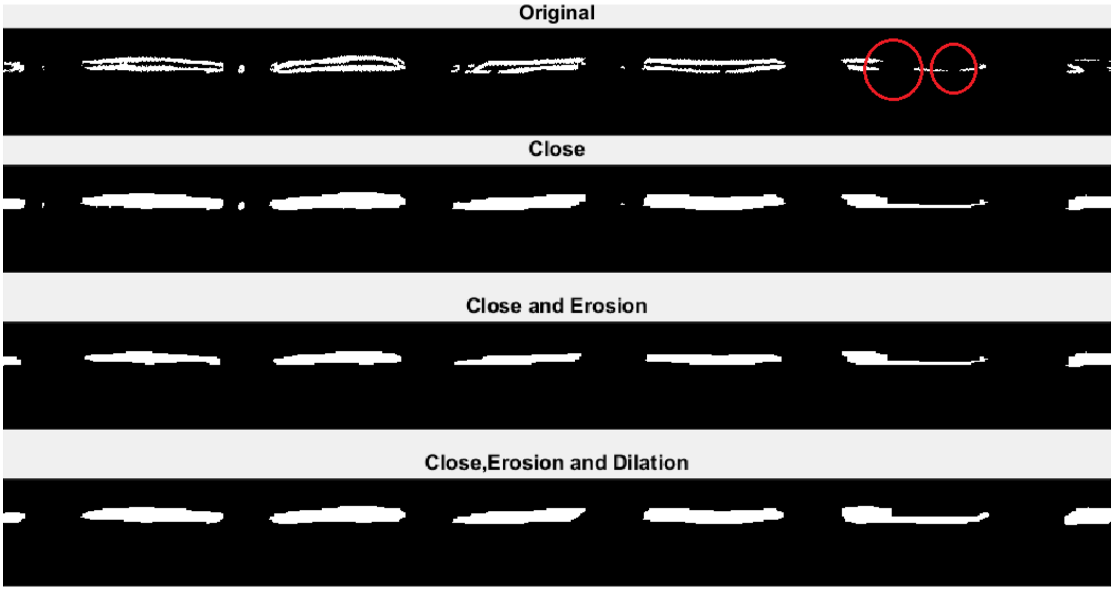

Figure 3.5: Morphological operations applied in path based approach to sinusoidal channel

3.3 Methodology steps

We have explained different section of the research methodology applied in this research work. Finally we summarize the methodology in few steps in order to understand easily.

- Original video sample is recorded by a high speed camera Mikrotron MotionBlitz MC1370 with 1000 fps of the air-water flow through a sinusoidal channel
- Two approaches were taken to measure the number of bubbles and velocity for analysis of fluid flow
- One approach is the processing of the original video sample
- The other appraoch is transforming the sinusoidal channel to a straighterned horizontal channel terms as path based approach Path based approach is a linear model of the sinusoidal channel to study non linear motion into non uniform linear motion

- Both channels were divided into different sections to illuminate the noise distribution easily, this is called image segmentation
- Different structuring elements of morphological operations in different segments were applied in the pre-processing operations
- Pre-processing will result in solid bubble contours from rough round bubble boundries and incomplete shapes
- In post-processing blob analysis is used for bubble detection and Kalman filter is used for bubble tracking Results information were taken for both sinsoidal and straightened horizontal channel which will be discussed in chapter 4.

Chapter 4

Results and discussion

Videos samples of non-convergent sinusoidal channel having different size and velocity of air bubbles with camera speed of 1000 frames per second were processed in MATLAB R2016a with Intel Xeon(R) x64 based processor having four cores of 3.3 GHz dell Power Edge T30. A total number of 75 test cases were processed and tracked each for sinusoidal curve channel and path based approach of straightened horizontal channel from 17 different videos of different bubble size and speed. Fig 4.1 shows different bubbles size with different speed in both channels. In (a) aspect ratio of air to water flow rate is higher resulting larger bubbles, a region shown by red circle where originally two bubbles tracked as two by path based approach and one bubble by sinusoidal approach. In (b) Air to water flow ratio is medium, here four bubbles are shown, tracked as four bubbles by path based approach and three in sinusoidal channel. Similarly in (c) Equal aspect ration of air to water flow rate here two bubbles are occluded due to channel noise, tracked as two by path based approach while it is not distinguishable in sinusoidal channel.

4.1 Measuring number of bubbles

We counted number of bubbles for each sample video S_i manually by an expert , and then tracked every sample through a Kalman filter with both sinusoidal chan-

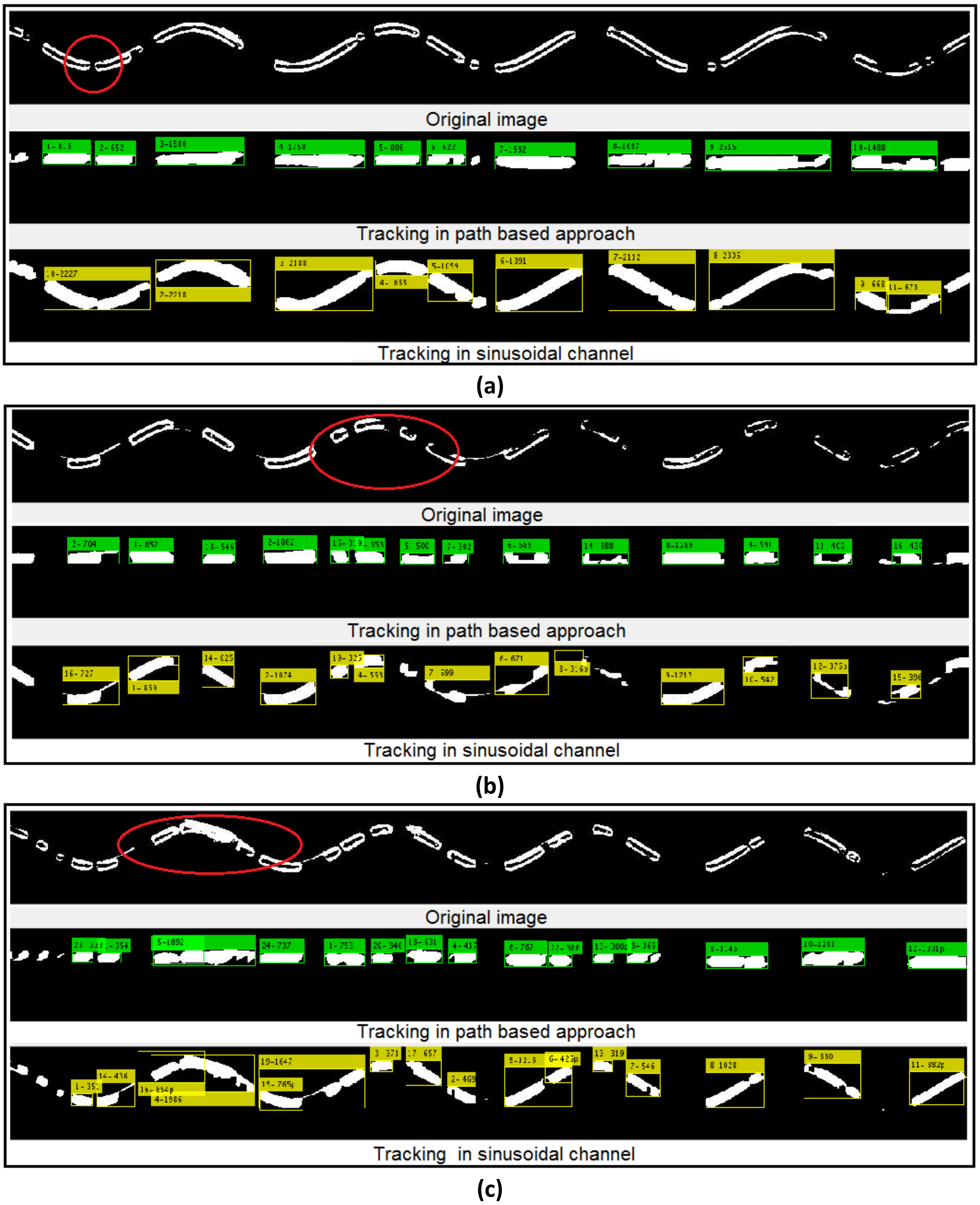

Figure 4.1: Different flow samples tracking in both path based and sinusoidal channel (a) Higher ratio of air-water flow rate (b) Medium ratio of air-water flow rate (c) Lower ratio of air-water flow rate

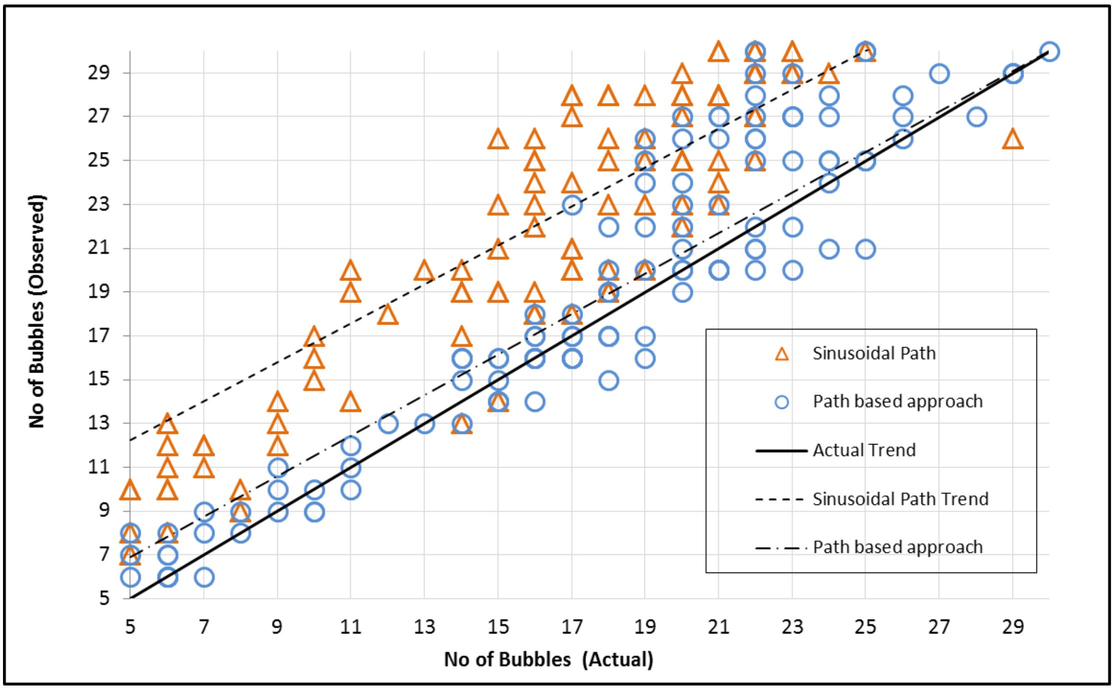

Figure 4.2: Comparing results of tracking for bubble count

nel and path based straightened horizontal channel. Tracking results for counting the number of bubbles is compared between these non linear motion model sinusoidal channel and non uniform linear motion model straightened channel with actual number of bubbles is shown in Fig 4.2.

It is clearly seen that trendline of path based straightened channel is very close to the Actual trendline measured through manual counting with naked eye . while curved channel trendline exceeds the original trendline.

4.2 Measuring velocity

Fig 4.3 shows experimental velocity along with computational velocity calculated for both sinusoidal curved channel and path based approach to the sinusoidal curved channel. A total number of 21 videos samples for different velocity and bubble size were processed. We first calculated the average velocity of a single bubble and then averaged all velocities of all bubbles in a sample video S_i. We clearly see that velocity estimation by Our approach having non uniform linear

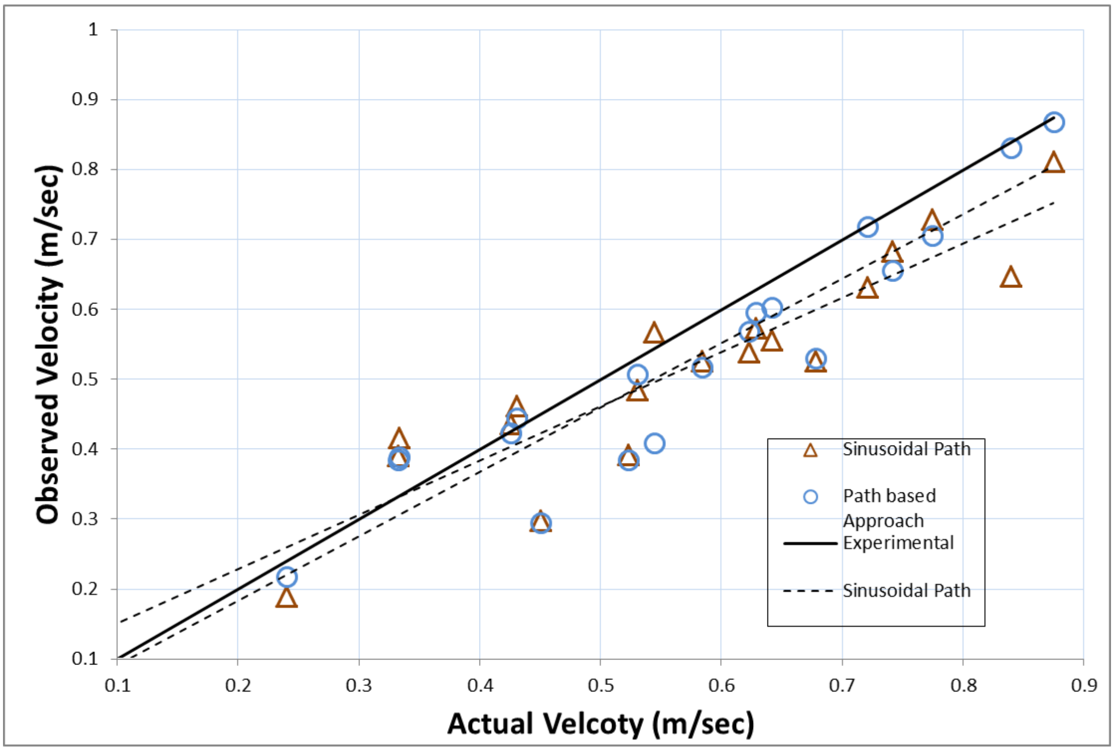

Figure 4.3: Velocities comparison for both sinusoidal and path based approach

dynamic motion model is more accurate than sinusoidal Channel which is non linear motion model.

4.3 Discussion

The reason that curve channel is not tracking the bubbles correctly is due to its non linear motion model. Bubbles flow in sinusoidal channel from top to bottom if any bubble gets occlude then Kalman filter estimates motion in the tangent line of the curve thus information of this bubble is missed. While in straight channel since motion model in non uniform linear across the straight line a little occlusion does not results missing of the bubble since motion estimation is done through a straight line and bubbles information are retrieved correctly. This is shown in Fig 4.5 at frame number (f_i) 13, bubble number 4 is shown, during its motion it occludes at f_i 32.At f_i 40, the bubble information is missed since the bubble is not moving through a tangent line, where Kalman filter estimates its motion along

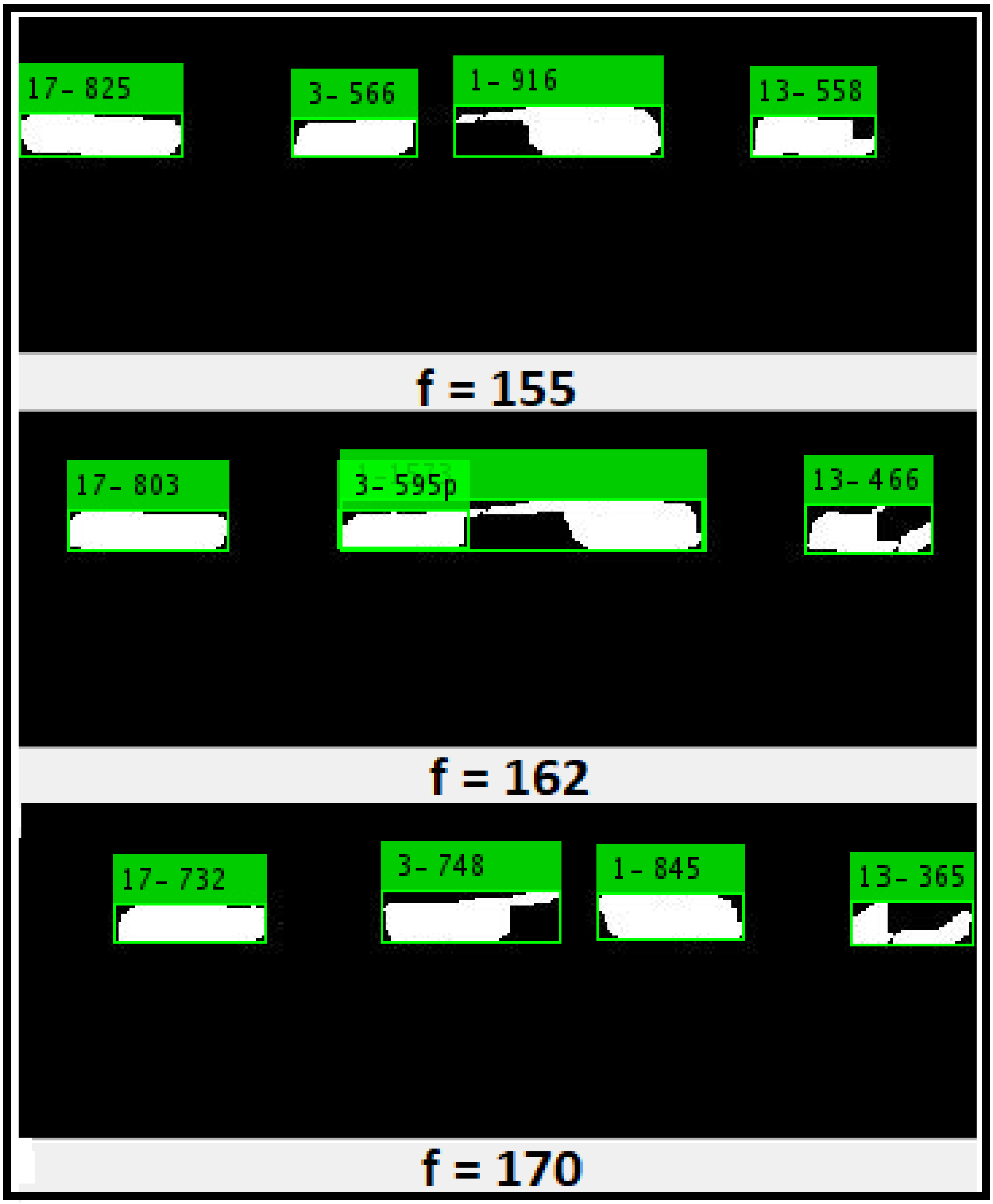

Figure 4.4: Kalman based motion estimation in our path based linear channel

that tangent line which is incorrect. Same case of occlusion for our path based linear motion model approach for bubble 1 and 3 is shown in Fig 4.4 at f_i 155, now at f_i 162, both bubbles occludes and at f_i 170, information of both bubbles are retrieved successfully. Moreover the morphological filling of the bubbles in the sinusoidal channel does not results in individual entity of bubbles but sometimes one bubble splits in two or more bubbles this can be also shown in Fig 4.5 where a bubble 4 information is missed and two new bubbles 5 and 6 are shown while in actual it is the same bubble 4. This also effects to calculate computational velocity for sinusoidal Channel.

The percentage error of both sinusoidal channel and path based approach to sinusoidal channel for both bubbles count and velocity estimation is given in Fig 4.6 and 4.7 respectively. The average percentage error in sinusoidal channel was 35.14 % for bubble count and 39.38% for flow velocity, while for path based approach to sinusoidal channel the percentage error was 10.29% for bubble count and 11.29% for flow velocity.

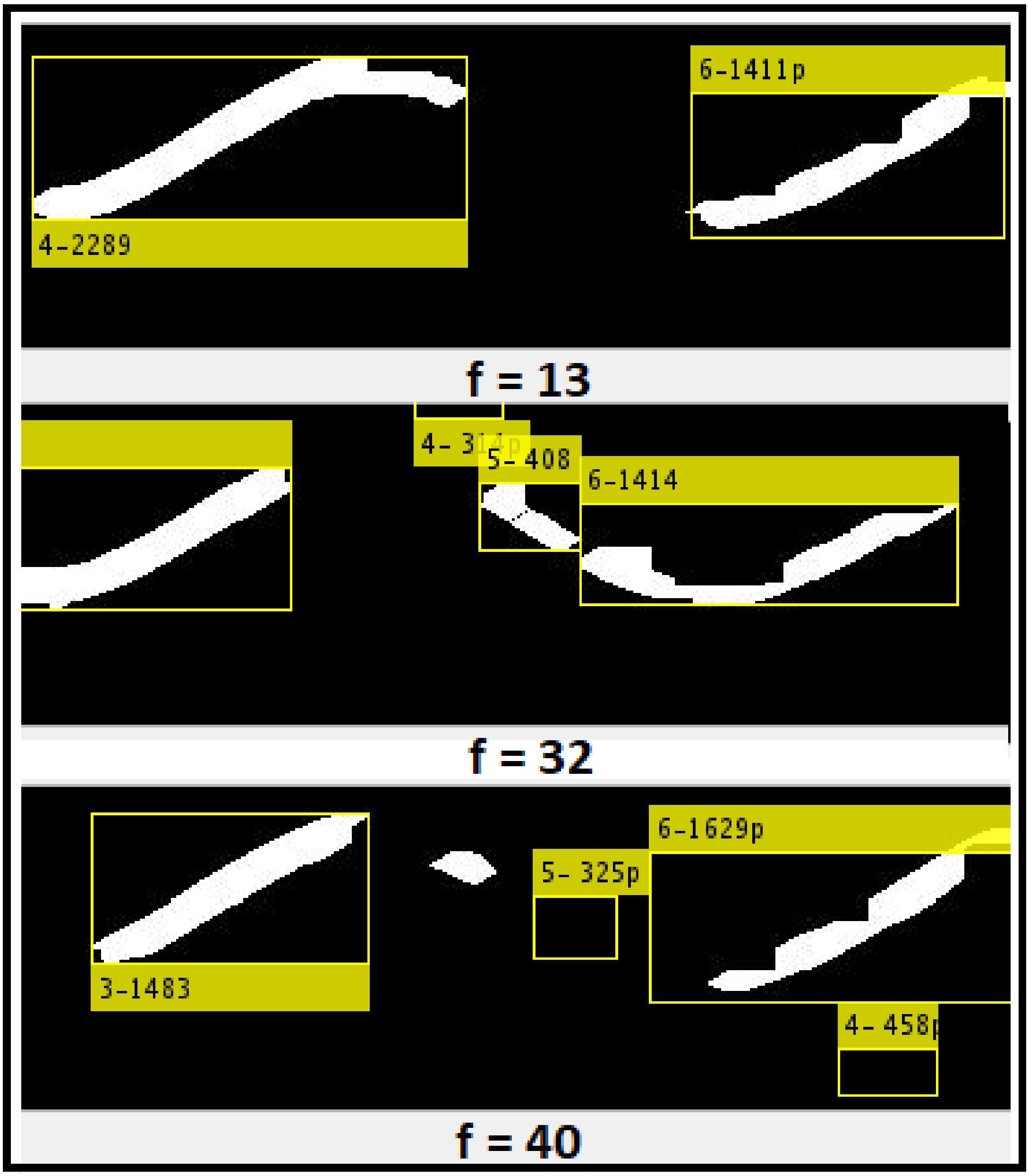

Figure 4.5: Kalman based motion estimation in sinusoidal Channel

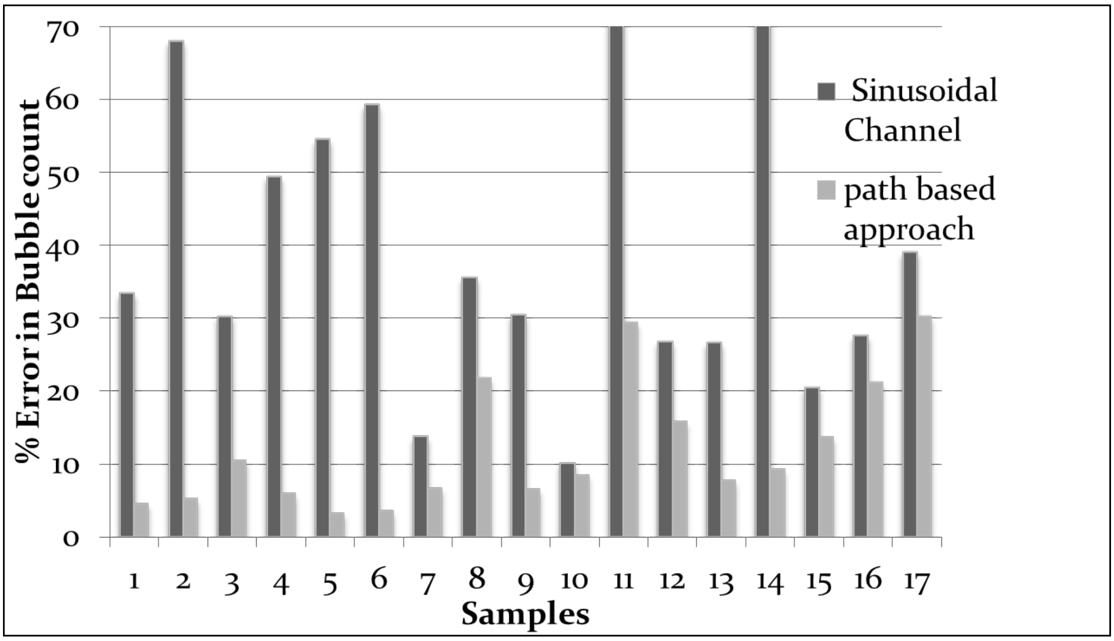

Figure 4.6: Percentage error in velocity calculation

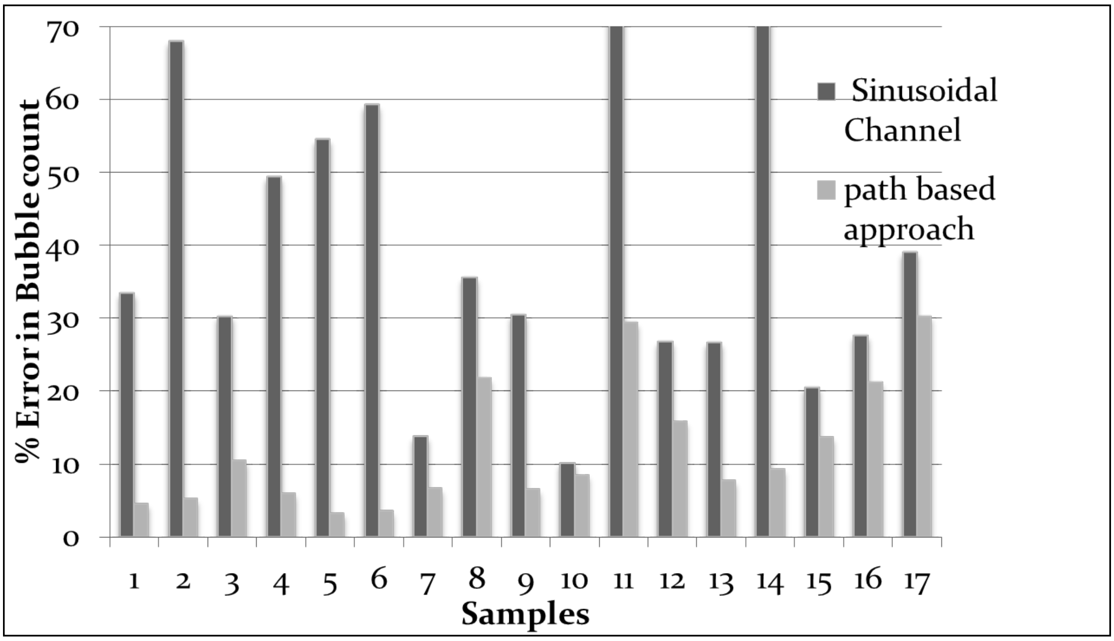

Figure 4.7: Percentage error in calculating bubbles count

Chapter 5

Conclusion

We have discussed here finding the flow parameters like number of bubbles, velocities for a non linear sinusoidal channel and approached the problem with a simple linear approach by a straightened channel to study the mass dispersion of gas liquid two phase system. It was shown that despite the geometric and appearance based techniques our approach of straightened channel has better results to define a bubble contours with simple segmented morphological operations and blob analysis. Finally the detected bubbles were tracked through a Kalman Filter and, it was shown that Our approach is more accurate and robust for calculating the bubbles and estimating the flow velocity than the curve channel. So we conclude this research as,

- Computer vision techniques of data acquired through high imaging sensor has been discussed
- Motion analysis of non Convergent sinusoidal channel is done through computer vision techniques
- The non linear sinusoidal channel is solved by path based approach, a linear model having the behavior of non linear motion
- Bubble boundaries were identified by morphing them efficiently
- Channel noise was removed by segmented morphlogical operations

- Both non convergent sinusoidal channel and path based approach to it was tracked through a Kalman filter.
- Kalman filter has a better response for analyzing the data through the path based approach
- The percentage error in the sinusoidal channel was 35.14% for bubble count and 39.38% for flow velocity, while for path based approach to sinusoidal channel the percentage error was 10.29% for bubble count and 11.29% for flow velocity
- Error reduction by path based approach was $\tilde{2}$0-25 % for bubble count and $\tilde{2}$2-28 % for flow velocity
- Overall path based approach has better response for measuring bubble parameters and presents a linear study of the non convergent sinusoidal channel

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