

MULTIPLE PHASE FLOW IDENTIFICATION USING COMPUTATIONAL  
SIMULATION AND CONVOLUTIONAL NEURAL NETWORK

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## **DEDICATION**

This project report is dedicated to my parents, who encouraged me to pursue my dreams and supported me during my journey. A special feeling of gratitude to my beloved sisters who stood by me throughout the process of achieving this Master degree. They all taught me that a dream doesn't come true unless by determination and hard work.

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## ABSTRACT

The Identification of gas-solid flow characterization in dense-phase pneumatic conveying particles is very important to a vast area of industrial fields such as chemical and pharmaceutical industries since a slight change in flow characteristics results in a completely different product. The motion of the gas-solid two-phase flow in dense-phase usually has a nonlinear and unsteady nature that needs to be examined and analysed to identify the particle flow behaviour in the pneumatic conveying pipelines. In this research a method to identify the type of flow pattern is proposed using a computational method where a gravity flow rig is modelled on Solidworks and multiple flow patterns are simulated with different mass flow rates ranging between 200 to 600 g/s. For changing the flow patterns inside the pipe, an Iris Mechanism is designed according to the specifications of the flow required to achieve the flow pattern control. A sectioning method is implemented to capture flow images at the plane of interest for different flow patterns. Afterwards images are fed to a Convolutional Neural Network which is trained and tested to identify the flow patterns according to several flow features which resulted in 100% accuracy. A GUI using PyQt is designed to better visualize the whole system and view the predicted flow pattern.

## ABSTRAK

Pengenalpastian ciri aliran pepejal gas dalam fasa zarah padat pneumatik sangat penting bagi kawasan industri yang luas seperti industri kimia dan farmaseutikal kerana sedikit perubahan ciri aliran menghasilkan produk yang sama sekali berbeza. Pergerakan aliran dua fasa pepejal gas dalam fasa padat biasanya mempunyai sifat tidak linear dan tidak stabil yang perlu diperiksa dan dianalisis untuk mengenal pasti tingkah laku aliran zarah dalam saluran penyampaian pneumatik. Dalam penyelidikan ini kaedah untuk mengenal pasti jenis corak aliran dicadangkan menggunakan kaedah komputasi di mana rig aliran graviti dimodelkan pada Solidworks dan pelbagai corak aliran disimulasikan dengan kadar aliran jisim yang berbeza antara 200 hingga 600 g / s. Untuk mengubah corak aliran di dalam paip, Mekanisme Iris dirancang mengikut spesifikasi aliran yang diperlukan untuk mencapai kawalan pola aliran. Kaedah pemotongan dilaksanakan untuk menangkap gambar aliran di bahagian yang dikehendaki untuk corak aliran yang berbeza. Selepas itu gambar disalurkan ke Rangkaian Neural Konvolusional yang dilatih dan diuji untuk mengenal pasti corak aliran mengikut beberapa ciri aliran yang menghasilkan ketepatan 100%. GUI yang menggunakan PyQt dirancang untuk menggambarkan keseluruhan sistem dengan lebih baik dan melihat corak aliran yang diramalkan.

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## LIST OF ABBREVIATIONS

UTM	-	Universiti Teknologi Malaysia
CFD	-	Computational Fluid Dynamics
NN	-	Neural Network
ANN	-	Artificial Neural Network
RNN	-	Recurrent Neural Network
CNN	-	Convolutional Neural Network
FFNN	-	Feed Forward Neural Network
RGB	-	Red, Blue, and Green
ESA	-	Electrostatic Sensor Array
2D	-	Two Dimensional
3D	-	Three Dimensional
LED	-	Light Emitting Diode
OFPT	-	Optical Fiber Process Tomography
ECT	-	Electrical Capacitance Tomography
ReLU	-	Rectified Linear Unit
GUI	-	Graphical User Interface

## LIST OF SYMBOLS

$\theta$	-	Theta
$\sigma$	-	Sigma
$\rho$	-	Rho
$\delta$	-	Delta
$\phi$	-	Phi
$\nabla$	-	Nabla
$\alpha$	-	Alpha
$\tau$	-	Tau
$\mu$	-	Mu
$\lambda$	-	Lambda
$\omega$	-	Omega
$\eta$	-	Eta
$\zeta$	-	Zeta

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# CHAPTER 1

## INTRODUCTION

### 1.1 Background Study

In 1826, a Norwegian mathematician called Niels Henrik Abel introduced a mathematical formula named after him, which is used in the analysis of spherically or axially symmetric functions [1]. His theory was implemented in image analysis where the forward Abel transform equation was used to project an optically thin, axially symmetrical emission function onto a surface, and the reverse Abel transform equation was used to measure the emission function centered on a representation of the emission function, which represents a scan of an image. Abel transform equations are restricted to systems of axially symmetrical geometries.

In 1914, the world came to know a new imaging method called Tomography, which was first introduced by the polish radiologist Karol Mayer [2]. His research was intended to fill in a gap for a new non-invasive medical imaging method. Not long after this date in 1917, Johann Radon, an Austrian mathematician used both Abel's and Mayer's theories to develop a new formula that works for both symmetrical and asymmetrical geometries [3]. Radon transform is an integral shift that takes a function  $F$  defined on the plane into a function  $R(f)$  defined on the 2D space of the plane lines, which on the line is equivalent to the integral line of a function on that line as shown in Figure 1.1 where  $\theta$  is the angle of the line.



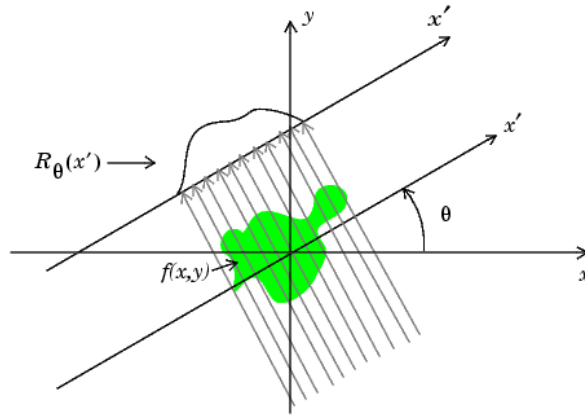


Figure 1.1 Radon Transform Theory

Following these theories, Sir Godfrey Newbold Hounsfield and Allan M. Cormack were awarded the Nobel prize in Medicine in 1979 for the invention of a computer assisted Tomography machine using X-rays [4], as shown in Figure 1.2. Their machine was used extensively in hospitals and medical imaging centers to help doctors in their diagnostics and was later developed into multiple other machines such as Computed tomography and Magnetic Resonance Imaging. The word tomography was driven from the Greek term "tomos", which means a section or a slice and "graphō", which refers to a picture. It was later identified as capturing multiple planes section images showing slices through an object. Every single slice is called a tomogram that is taken using a device called tomograph [5].



Figure 1.2 Sir Godfrey N. Hounsfield with his X-ray Machine

Years later, The tomographic methods were extended to industrial processes to provide more efficient process control and higher production rate. It can be found in many industries such as pharmaceutical, chemical and food processing industries. Electrical tomography is one of the most investigated fields in process tomography. It is non-invasive, cost-effective, safe and easy to implement the technique. Electrical charge tomography is a system used in particulate imaging flow in pipelines using electrodynamic sensors (charge-to-voltage transducers). It is a passive transducer where the flowing solid particles generate the field.

The idea behind process tomography lies beyond a simple concept. An even number of sensors are fixed around a pipe separated with equal angles to capture tomograms for the plane of interest. Particles concentration signal data is passed from the sensor to a computer for analysis and reconstruction of images.

The use of process tomography is not limited to only obtaining a cross-sectional image of processes. It can also be used to obtain velocity profiles and mass-flows rate or volume flow rates depending on the sensing mechanism used process tomography can be used in processes involving solids, liquids, gases and any of their mixtures [6].

## 1.2 Problem Definition

The motion of the gas-solid two phase flow in dense-phase usually has a nonlinear and unsteady nature, as shown in Figure 1.3, that needs to be examined and analysed to identify the particle flow behaviour in the pneumatic conveying pipelines.

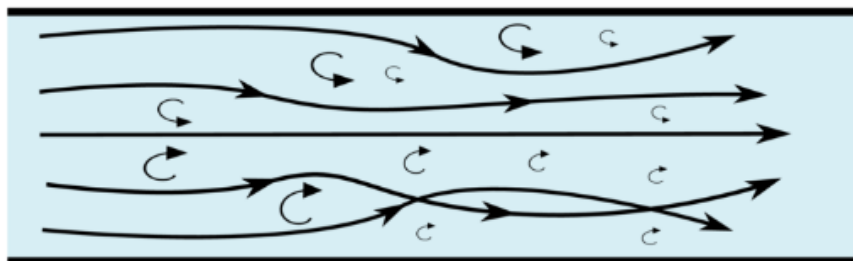


Figure 1.3 Dense Phase Flow

Various researches were done in this field using tomographic sensors such as Electrostatic Sensor Arrays and other similar techniques. This study focuses on applying the Computational Fluid Dynamics techniques in a simulation environment to accurately identify the type of flow using various other parameters.

### **1.3 Project Objectives**

Five objectives were considered in this project which are:

- Design and Simulate the Flow identification experimental setup in the simulation software.
- Design an Iris Mechanism to control the type of flow pattern.
- Simulate different types of flows with the same environmental parameters.
- Collect the flow pattern images using the Flow simulation tool for different flow regimes.
- Apply a Convolutional Neural Network (CNN) for flow pattern identification.

### **1.4 Project Scope**

The scope of the project is as follows:

- 6 types of flow shown in Figure 1.4 will be considered in this study which are fully, three quarters, half, and quarter filled pipelines, as well as 2 Annular flows with pipe diameters 25 and 75 mm.
- A range of Mass flow rates will be considered starting from 200 to 600 g/s.
- Create a Convolutional Neural Network (CNN) for flow pattern identification.
- Create a Graphical User Interface using PyQt to visualize the results.

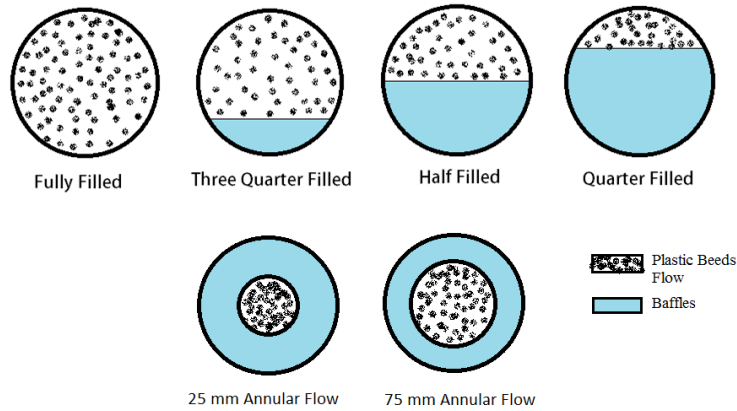


Figure 1.4 Six types of Flows

## 1.5 Organization of the Report

This thesis is divided into five sections. The introduction presents the principle aspects of the project, how they are implemented and their applications, in addition to defining the problem, objectives and the scope of the project. Literature Review introduces the most recent developments in the field of interest of the project where the latest research methods in the identification of multiple phase flow patterns are introduced. Methodology chapter includes the descriptive explanation of the methods used in this project in order to achieve the objectives. Results and Discussion section highlights the results obtained with a comprehensive discussion about the findings. The last section is the conclusion where the last comments about the project as well as the future work are presented.

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