Flow Regime Identification and Concentration Distribution of Solid Particles Flow in Pipelines using Electrodynamic Tomography and Artificial Neural Networks.

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Abstract

Solid particles flow in a pipeline is a common means of transportation in industries. This is because pipeline transportation can avoid waste through spillage and minimizes the risk of handling of hazardous materials. Pharmaceutical industries, food stuff manufacturing industries, cement and chemical industries are few of the industries to exploit this transportation technique. For such industries, monitoring and controlling material flow through the pipe is an essential element to ensure efficiency and safety of the system.

This paper presents electrical charge tomography which is one of the most efficient, robust, cost-effective and non-invasive tomographic methods of monitoring solid particles flow in a pipeline. Process flow data is captured fitting an array of 16-discrete electrodynamic sensors about the circumference of the flow pipe. The data captured is processed using two tomographic algorithms to obtain tomographic images of the flow. Then a neural network tool is used to improve image resolution and accuracy of measurements. The results from the above technique shows significant improvements in the pipe flow image resolution and measurements.

1. Introduction

Tomography is a Greek term which stands for cross-sectional picture. It involves obtaining of cross-sectional image of a body or a process. One of the earliest applications of tomography is in the field of medicine where a particular plane in human body is imaged using this technique for diagnosis purposes.

The application of tomographic methods in industries for the purpose of better process control, optimization and efficient production is know as process tomography. Though the birth of process tomography only dates back little more than two decades, it has found application in various industries such as chemical, oil, gas, food processing, biomedical, pharmaceuticals, and plastic products manufacturing.

The use of process tomography is not limited to only obtaining cross-sectional image of processes. It can also be used to obtain velocity profile and mass-flow rate or volume-flow rate of the same process. Depending on the sensing mechanism used process tomography can be used in processes involving solids, liquids, gases and any of their mixtures.

Process tomography can be applied to many types of processes and unit operations, including pipelines, stirred reactors, fluidized beds, mixers and separators. Depending on the sensing technique used, its non-invasive, inert and non-ionizing. It is therefore applicable in the processing raw materials; in large and intermediate chemical production; and in food and biotechnology areas [1].

Electrical charge tomography is the particular tomographic method this paper is concerned with. Electrical charge tomography also know called electrodynamic tomography, uses electrodynamic sensors. Electrodynamic sensors are basically charge to voltage converters. Electrodynamic sensors consist of two major functional parts; the sensing electrode and the signal conditioning electronics. The function of the sensing electrode is to detect electric charge in its sensing region. Sensing electrode is a silver steel rod. The second functional part of the sensor is the signal conditioning part. This part is the electronic part and responsible for converting the charge quantity sensed by the electrode to its equivalent electrical signal (voltage). It consists of amplifiers, buffers and filters. An electrodynamic sensor is shown in figure 1 below.

The motivation for using electrodynamic sensors as the sensing device in tomography arises from the fact that many flowing materials pick up charge during transportation, primarily by virtue of friction of fine particles amongst themselves and abrasion on the wall of the conveyor [2].

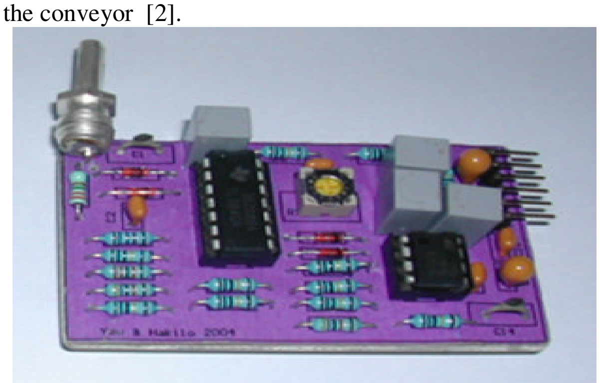


Fig. 1: An electrodynamic sensor

Although charge generation on solids and powders is well know from electrostatics, it is not generally possible to calculate the magnitude of charge generated solely based on the properties of the material and the process in which its involved.

However, it is know that the magnitude of charge generated depends on different parameters.

It has been established that the magnitude of charge acquired by solids depends upon the moisture content of the atmosphere, the particles size distribution and the velocity with which the particles move and/or impinges onto surface [3].

2. Data Source

The main source of data in this project is the gravity flow rig. The flow rig consists of a tank, a hopper, material feeder vane, flow pipe and an array of electrodynamic sensors mounted on the flow pipe. An automatic vacuum loader is used to transport the solids material from the tank back to hopper as the tank gets full. Figure 2 below shows the laboratory gravity flow rig.

Plastic beads of mean size 3mm are fed down the pipe through the feeder. Since the plastic bead particles are accelerated only by the force of gravity, their velocity (v) as they pass the sensor array can be calculated as equation 1.

$$V=\sqrt{u^2+2gs} \qquad (1)$$

u is the initial velocity, which is 0 in this case.

g is gravitational acceleration which is a constant 9.8 ms^{-1}

s is the distance from the feeder to the array of sensors which is 1.4m.

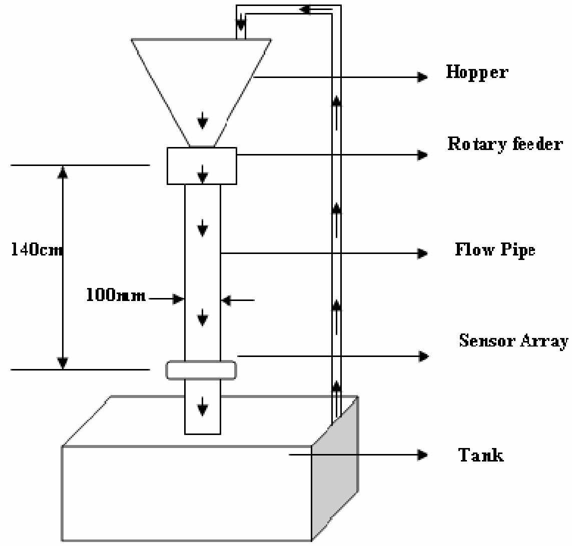


Fig. 2: Gravity flow rig

Therefore the velocity of the particles as they pass the sensors array is 5.24 ms^{-1}.

The flow rate of the plastic beads is controlled by the rotary valve through the control unit.

3. Data capture and storage

Sixteen similar electrodynamic sensors are fitted equi-spaced around the circumference of pipe 1.4 meters from the feeder. Each electrodynamic sensor is fitted to the outer pipe wall and is insulated from the metal pipe wall. The electrode on each sensors detects charge as the charged particles flow past it, and the electronic circuitry of the sensor converts this physical quantity (charge) to its equivalent electrical quantity (voltage). Thus each sensor gives information about distribution of particles in its sensing zone. Each sensor produces 3 types of output namely; ac signal, average dc and rectified signal.

Information from the 16 electrodynamic sensors is received and stored on a computer memory by high speed data acquisition card (DAS1800). Signal from each sensor is converted to digital signal at 1000 samples per second and made available for further processing.

Averaged signal from the sixteen sensors output is the signal of interest in this material. This is the output needed to produce tomographic images of flow. However the ac signal can be used for extracting information related to velocity profile. And the rectified signal output for spatial filtering purposes.

The spatial filtering effect can be defined as the relationship between sensor size and the frequency bandwidth of the transducer determined from the frequency response obtained during a pulse which corresponds to a detectable particle[4].

4. Image reconstruction algorithms

The goal of reconstructing tomographic images from the captured data is achieved through image reconstruction algorithms. Here two kinds of reconstruction algorithms are used. Linear back projection algorithm (LBPA) and filtered back projection algorithm (FBPA).

The tomographic measurement data is manipulated using algorithms for image reconstruction, profile analysis and numerical quantities such as flow rates, concentration, size and phase distribution [5].

The tomographic image is calculated from the measurements data using a filtered back-projection algorithm, which is derived from forward problem [6].

To solve the forward problem, firstly the cross-section of the pipe is mapped onto an 11 X 11 rectangular array consisting of 121 pixels as shown in figure 3 below.

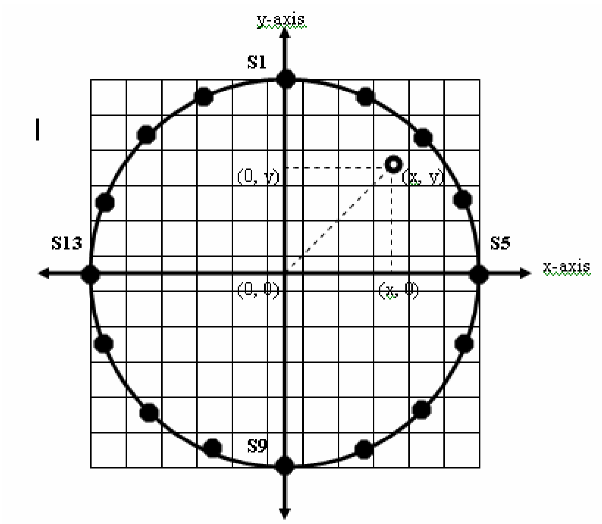


Fig.3: The 11 X 11 rectangular array mapped on the pipe

Then assuming uniform surface charge distribution of C coulombs per square meter (C m^2) on each 121 pixels, the theoretical output of each sensor is determined.

The sensitivity map of each sensors is calculated according to equation 2, when the center of the pipe has rectangular coordinate (0,0).

$$e1= \iint \frac{C}{r2} dA = \int_x dx \int_y \frac{C}{x2+(50.5-y2)} dy \qquad (2)$$

where r is point charge to sensor distance and A is pipe cross-sectional area. The total charge induced on each sensor when C is assumed to read 1 C m^2 is calculated as follows:

$$e1= \int_{-50.5}^{50.5} dx \int_{-(50.5-x2)1/2}^{(50.5-x2)1/2} \frac{1}{x2+(50.5-y)2} dy \qquad (3)$$

The sensitivity map of each sensor is multiplied by its sensor reading and the value of similar pixel from the 16 matrices are summed to provide a charge concentration map of 11X11 matrix. This is the tomographic image calculated according to linear back projection algorithm. However as theoretical values indicated, the algorithm seems to give less weight for pixels further away from the sensors even when uniform charge distribution is assumed. This situation is remedied by applying filter masks to give compensation values for pixels away from the sensors. Combining the images obtained using linear back projection algorithm with the filter masks gives filtered back projection algorithm images which are of higher resolution and better representation of the flow.

Prior to applying filter mask, knowledge of flow pattern being conveyed is necessary as filter masks for various flow patterns are different. Due to the nature of gravity flow rig its impossible to know the type of flow regime being conveyed. However, neural networks can be trained on artificially created flow regimes, to later classify flow regimes being conveyed normally by the gravity flow rig after training.

5. Artificial Neural networks

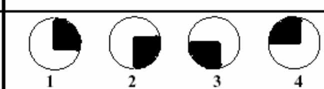
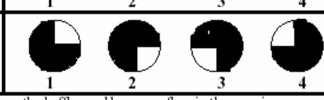
An artificial neural network (ANN) or simply neural network is an information processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information. Its built from a large number of
central processing units (neurons) interconnected to perform parallel computation. Unlike conventional computers ANN's are based on the concept of distributed, adaptive and non-linear computing.

The main objective of using neural network is to determine the type of flow regime being conveyed from sensors output data directly without need of image processing step. This technique have two important contributions; a significant amount of competition time otherwise needed for image processing is saved and a filtered back projection image reconstruction algorithm can be used and hence higher accuracy tomograms are obtained.

The flow regime identification task of this work is accomplished by using neural network technique due to two reasons. One is, there are not many standard flow pattern identification techniques apart from a statistical method. The statistical method compares the mean, average, variance and other information of the data to classify the various patterns into groups (much like visual inspection). This technique lacks the reliability to classify complex patterns such as tomographic data into pre-defined target groups. The second reason to use neural network technique in preference to other techniques is that neural networks are a proven noise resistant technique and hence their suitability for noisy electrodynamic tomography data classification.

Here a back propagation network with a hidden layer of 8 neurons, biases, 16 input neurons and 4 output neurons is trained on artificially produced patterns. Data from the 16 electrodynamic sensors is used as inputs and binary codes representing artificially created full-flow, three-quarter flow, half flow and quarter flow patterns are used as targets to train the network.

Table 1: The different flow regimes along with the baffles used and their binary codes.

No.	Flow regime	Baffles used	Binary codes
1	Full flow	No baffle needed	1111
2	Three-quarter flow		1 -0111 2 -1011 3 -1101 4 -1110
3	Half flow		1 -0011 2 -1001 3 -1100 4 -0110
4	Quarter flow		1 -1000 2 -0100 3 -0010 4 -0001

* **note**: the dark regions show the baffles and hence no flow in those regions.

There are 4 types of flow regimes to identify each with 4 variations. Therefore four bits binary code is sufficient to represent all the variations and is used as target vectors. The inputs to the neural network are output voltages captured by the sensors as a result of charged solid materials presence in the measurement cross-section.

There are no sets of rules as to what values the network's parameters should be set to initially. But there are guide lines to follow when initializing these parameters. Therefore the network parameters in this work are optimized after various experiments are carried out.

Feed forward network with back propagation learning function as described above is trained on the data collected from the flow rig. The network initially produces large error (the difference between actual output and target output). This error is back propagated from output through hidden layer and the weights of these two layers are iteratively adjusted. As more data is passed through, the error level is reduced till it reaches the minimum acceptable error. Now at this point training is stopped and the network is used in classifying data from the gravity flow rig directly.

6. Results

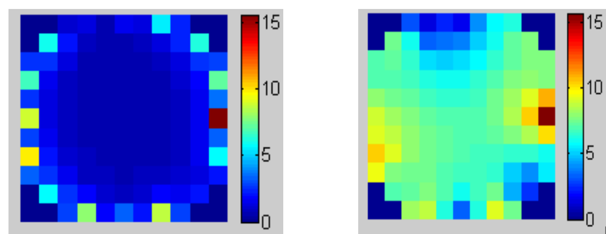
The performance of the network after training for 3000 iterations is illustrated in figure 5. The performance goal was set to 1e-4 and maximum epochs to 3000 but the network has reached the goal in 325 epochs.

As the training function used at the output layer is log sigmoid, the output of the network is bound to a value of 1 to 0.Typical outputs of the network are shown in table 3.

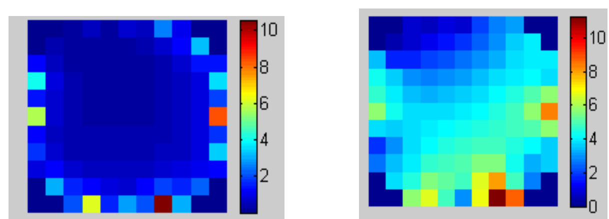
Concentration profiles of the solids conveying in the gravity flow rig is produced using the two tomographic reconstruction algorithms; linear back projection algorithm (LBPA) and filtered back projection algorithm (FBPA). The tomographic images captured at various flow rates are shown below.

Table 2: typical out put of the network of figure 4.

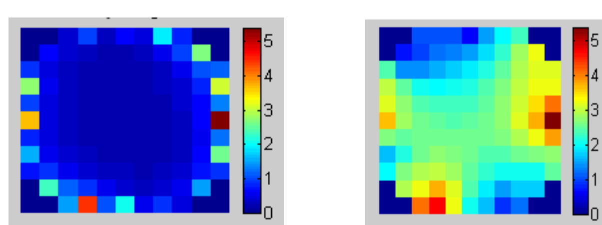
Flow type	O/P 1	O/P 2	O/P 3	O/P 4
Full flow	0.9960	0.9859	0.9882	0.9835
Three-quarter flow	0.9913	0.9874	0.9857	0.0119
Half flow	0.9987	0.9937	0.0082	0.0026
Quarter flow	0.9915	0.0124	0.0071	0.0014



a (LBP) b (FBP)
Fig 4: Full flow at 58 g/s.



a (LBP) b (FBP)
Fig. 5: Half flow at 83 g/s.



a (LBP) b (FBP)
Fig. 6: Quarter flow at 58 g/s.

7. Discussions and conclusions

The methodology and the results obtained above shows that electrical charge tomography is a cost effective, robust and convenient means of solids flow measurement technique. The limitation of electrodynamic sensors is found out to be non-linear sensing. That is it reads less values as the charged solids flow further from the sensor locations. This situation is shown in figures 4 (a), 5 (a) and 6 (a) where solids concentration at the center of the pipe seemed always low.

This main disadvantage of electrodynamic sensors is shown to be compensated for in the second algorithm which must use neural network technique.

Feed forward network with back propagation learning algorithm is also shown to be able to determine flow patterns which is a necessary step in applying filtered back projection algorithm.

The flow images obtained using filtered back projection algorithm, shown in figures 4 (b), 5 (b) and 6 (b), are of more higher resolution. This in turn improves the accuracy of different solids flow measurements such as concentration profile, velocity profile and hence mass-flow rate profile.

References

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