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Pipe clogging in the fertilizer industry, opportunities and challenges for computer vision

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Abstract: In the context of industry 4.0 where the use of new technologies is required to meet productivity and profitability demands, this paper addresses 3D scanning, thermal imaging and computer vision to identify pipe clogging caused by waste accumulation in the fertilizer industry. This paper presents a study using thermal images and the use artificial neural network to model the waste distribution in industrial pipes.

Keywords: Computer vision; image modelling; industry automation. Infrared detectors; fertilizers.

1. INTRODUCTION

This paper involve the use of the visual computation in thermal images and 3D laser for inspection non-invasive of pipe in fertilizer industry. The paper proposes a model using artificial neural networks to determine the dust deposit profile in clogged pipes.

The Food and Agriculture Organization of the United Nations (FAO) informs that the increase in fertilizer production has an average annual growth of 1.9 percent, and a production of 201.66 million tonnes by the end of 2020 is expected FAO (2017).

The fertilizer industry has been demanded not only for more productivity, but also for better quality and customized solutions. In this scenario, technological advances in software and hardware bring greater capabilities to operations, smart factories or Industry 4.0 is focused on integrating technologies to promote increased productivity and operational efficiency Saunila et al. (2019).

The production of fertilizers takes place in basically three stages: production of raw and basic materials, basic fertilizers and mixtures, and the last stage is responsible for mixing according to the particular requirements of the soil, composing the bulk blend fertilizers Miserque and Pirard (2004).

This mixing happens inside the ducts in the factory and the chemical substances are in the form of dust/powder. The dust in the presence of heat and moisture chemically reacts forming a sediment that can obstruct the duct and compromise the whole function of the industry machinery. In fertilizer production, pipeline systems are very heavily loaded by aggressive transport. The build-up of deposits and impurities is favourable in these conditions.

The manual pipeline cleaning is necessary to unblock the duct, with this, the production stop occurs, causing the total stop of the factory with significant loss in the company's profits. The maintenance of clean pipelines is of great importance for the continuity of the production process.

The idea is to use thermal images and 3D laser to model the accumulation using Neural Network (NN) Algorithms. Due to the inhospitable feature of the environment we propose a scaled dataset where a scale pipe mockup is used to simul different obstruction pattern. We use the thermal camera to image the pattern and the 3D scanner to obtain the ground truth associated with the accurate dust deposit (label). Thus the NN can learn to map the thermal image (input) in a precise depot model (label). The scaled model was applied to developed to map the external thermal behavior and the deposit profile in a controlled environment and determine parameters for the real case application in a large fertilizer company located in the south of Brazil.

The Thermography is a non-destructive and non-invasive remote sensing inspection technique that enables temperature measurement and thermal imaging of a component, equipment or process from infrared radiation. This monitoring is able to provide sufficient data for trend analysis without interrupting the production cycle.

Recently, visual computing technology has been widely used for non-invasive inspection applications in industry Moreno et al. (2017), Posada et al. (2015), Stork (2015). Technologies such as digital cameras, thermal cameras, augmented reality and 3D laser scanning made possible the acquisition, analysis and synthesis of visual data through the use of computer resources, Stork (2015). In this work we use two of these technologies, thermal camera and 3D laser scanner.

In this paper a novel non-invasive thermal-based inspection technique is used to model the pattern of the closure of dust pipelines due to fertilizer accumulation inside.

This paper is organized in five sections: This introduction about subject. Section II is a brief about Visual computing and artificial neural networking. Section III is the methodology where NN algorithms are development to map image to depot profile. Section IV the algorithms are applied in test and validate, the discussion of obtained results. Finally, and conclusions are introduced.

2. VISUAL COMPUTING AND ARTIFICIAL NEURAL NETWORK

There is a worldwide movement in some of the most advanced economies seeking to improve industrial manufacturing productivity and efficiency by incorporating the latest advances in Information and Communication Technology (ICT) combined with artificial intelligence mechanisms, Posada et al. (2015).

For the future of production, academics and professionals anticipate significant efficiencies mainly through the consequent digital and intelligent integration of manufacturing processes, Zhou (2013).

2.1 Computer Vision

In the next few years, computer vision should be increasingly present on the shop floor, being an important investment to increase the productivity and competitiveness of industries. Accurate computer analysis can save industry time and improve quality. Because of this, visual computing is considered one of the keys to achieving industry 4.0 Stork (2015), this technology involves capturing, analyzing, and synthesizing visual data through computational technology Posada et al. (2015), including techniques for computer graphics, such as real-world object modeling and simulation, human-machine interaction, image processing, and more Stork (2015).

Thermography. Thermography is a technique for obtaining images in which the infrared spectrum is adopted to measure the heat emitted by an object Chen et al. (2015). This technology uses pseudo-color image processing to describe the surface temperature distribution of an object of interest. Measurement systems are calibrated to provide accurate temperature information for each detector pixel. Colors are obtained according to the calibration adopted to represent temperatures in the infrared spectrum Acampora et al. (2011). Thermal images produce color or gray images of infrared rays invisible to humans or heat radiation. This allows the measurement of temperatures without the need for any contact with the target object, i.e. a noninvasive technique Zadeh et al. (2016).

The most recent contributions related to the application of Infrared thermography (IRT) in the industrial context are classified into three main groups, namely, electrical, mechanical and other applications; however the application of thermography is not limited and its application has been appearing in other fields Osornio-Rios et al. (2018). One of the advantages is that the thermography is not destructive, it is not necessary to stop the machine and disassemble it to see the condition of any component or process.

The 3D Laser Scanner. With Laser Scanning 3D, we have a reality "clone" that makes it possible to identify details. Studies, projects and research carried out with data obtained from the Laser Scanner guarantee a higher level of detail and, consequently, the product made from them can be richer and more assertive.

A laser stripe is projected onto a surface and the reflected beam is detected by CCD cameras. Through image processing and triangulation method, three-dimensional coordinates are acquired. The laser probe is mounted on a three-axis transport mechanism and moves along the scan path that consists of a series of predetermined line segments Son et al. (2002).

The Point Cloud in three dimensions is the most basic data of Laser Scanning 3D, from which we can perform modeling (2D or 3D) or the extraction of information to meet a certain purpose. Ebrahim (2016).

2.2 Neural Network

The neural network is inspired by natural biological systems, and if it is well-trained, it has a very high predictive ability. An artificial neural network is a computational method that, with the help of a learning process and the use of processors called neurons, tries to present a mapping between the input and the positive environment (output data) by recognizing the intrinsic relationship between the data.

A multilayer perceptron (MLP) is an example of a neural network. It is a model of interconnected nodes, or neurons, that is able to represent the map between input data and output data Gardner and Dorling (1998). Each connection between the neurons have weights and activation functions. The architecture of a MLP consist of different layers, one input layer, hidden layers and output layers.

A training data is required for the multilayer perceptron to learn. In the training step the MLP network is repeated and the weigths are adjusted until the desired mapping, Gardner and Dorling (1998).

The most common learning is the back-propagation algorithm. The back-propagation algorithm uses supervised learning. In supervised learning, when the input is applied to the network, the network solution is compared with the target solution designed for the network, and then the learning error is calculated and used to adjust the network parameters, Gardner and Dorling (1998), Esfe et al. (2015).

3. METHODOLOGY

In this work we proposed the use of a neural network to map thermal images to profile of dust. The idea is to use a NN to learn the relation between the pixel of the image into depth of accumulation.

The hypothesis is that the fertilizer is a less thermical material than the duct itself, it is possible to capture in the image the accumulation by the thermal behavior of the duct. The hypothesis can be evaluated in Figure 1. In this figure we can see the subtraction of different sets of thermal images, in pairs, resulting in diagrams and 3D representations of the gradient change in temperature of a surface. The thermal images were taken of the same pipe with different deposit profiles.

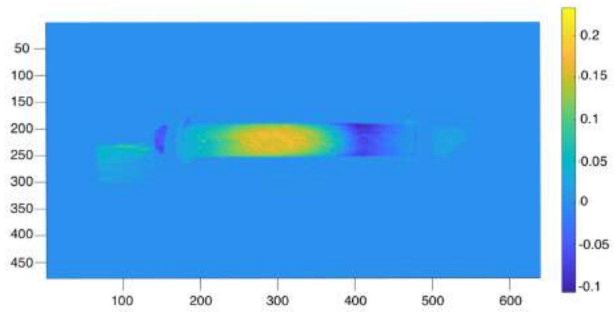

Fig. 1. Difference obtained from the subtraction of two thermal images where the pipe had different distribution of dust along it.

The result shown in Figure 1 was acquired through the pixel-by-pixel subtraction where one image had a uniform distribution of dust along the entire length of the pipe bottom and the second image the pipe was completely empty. We can observe that there is a significant difference in the thermal profile of the duct with a partial obstruction present, in contrast to the empty duct.

By subtracting two images we get a difference image which shows the movement of changes that have occurred in the scene Solomon and Breckon (2011a). This technique is used as a basic form of change/movement detection. We can observe in the figure that the temperature inside the pipe decreased with the addition of fertilizer, leading to an assumption that the fertilizer acts as a heat barrier. This points out that when the temperature in the duct decreases, an unwanted dust accumulation is occurring in the duct, which may adversely affect the whole operation of the fertilizer production.

We propose a Multi-layer Perceptron (MLP) Neural Network to map infrared images (input) into deposit profile (output). Figure 2 show the architecture of our NN. The NN has one input layer with n^2 neurons ($n_X n$ patch mask), a hidden layer and an output layer with one scalar neuron (Z of deposit profile).

To train the NN we propose a dataset. To obtain a dataset is very hard task. It is not easy to have a precise profile of the dust due to the inhospitable environment. The flow of the dust and confident prevent to measure the ground truth of the deposit. For that we propose a scaled dataset where a scaled pipe is used to simulate different profiles that are imaged by infrared cameras and 3D laser.

4. THE SCALED DATASET

Figure 3 shows an overview of the experiment to obtain our scaled dataset. Each sample of the dataset is composed by a thermal image (input) and a 3D profile of deposit (label).

4.1 Dataset Input: The Thermal Image

The thermal image was obtained by pointing the thermographic camera to the scaled tubing that had a heat

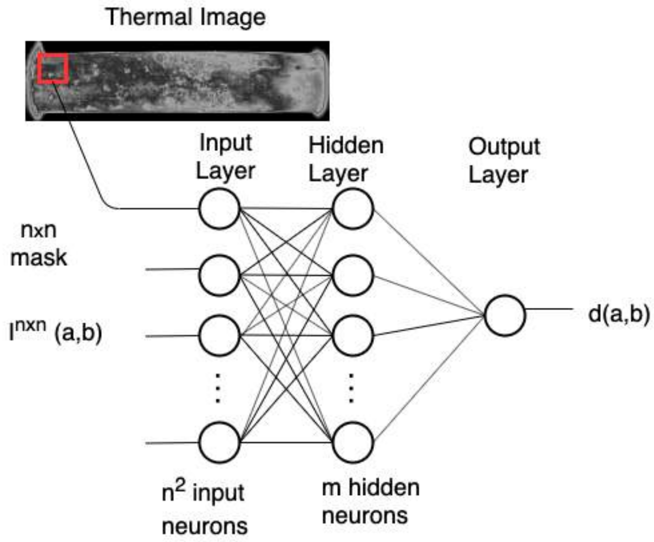

Fig. 2. Methodology of the mapping from the thermal to the deposit profile.

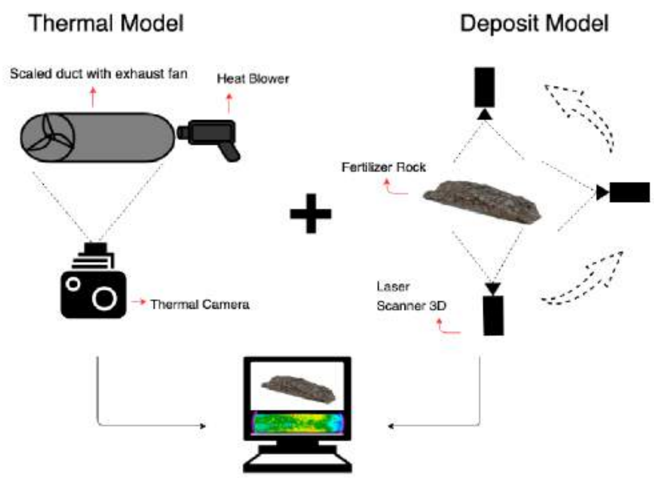

Fig. 3. Proposed method solution.

blower and an exhausting fan. The image processing was applied to the region of interest of the thermal image, which corresponds to the duct in study, to identify the thermal behavior.

Figure 4 shows an example of an infrared thermography image of the duct scale model captured in the experiment. While Figure 5 is the same duct but with fertilizer sediment inside de pipe.

4.2 Dataset Label: the deposit profile

The deposit profile $I^D(x, y)$ was obtained with a 3D laser scanner which was pointed to the object being analysed, in this case the object is the fertilizer sedimentation rock. The scanning is made by pointing the 3D laser scanner to the sediment and rotating it in a 360° spin around it, to scan all faces of the fertilizer sediment. One view of the scanned profile is presented in Figure 6. With the scanned object we are able to obtain the distance measurements of the rock in order to associate each patch of the thermal image to a deposit profile.

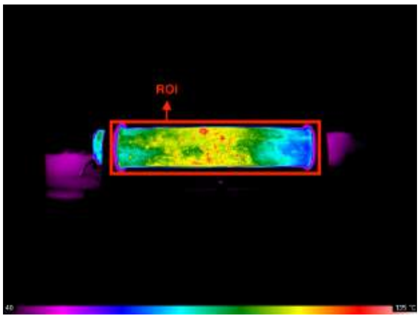

Fig. 4. Example of a thermal image obtained in the experiment when the duct was cleaned inside.

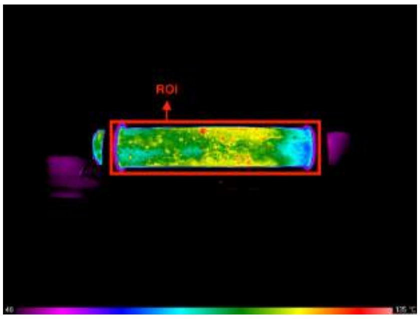

Fig. 5. Example of a thermal image obtained in the experiment when the duct had sediment inside.

Fig. 6. The fertilizer sedimentation.

4.3 Association with Thermal Images and Residual Profile

To obtain the deposit model, we get the fertilizer rock and scan it with the 3D laser scanner, Figure 6 presents an example of the scanned fertilizer sediment.

We need to find an association between a pixel in a thermal image and a Z_{height} of dust present on the pixel equivalent surface of the image. The scanned object is then sliced in order to calculate the distance between the points in each slice, as in Figure 7.

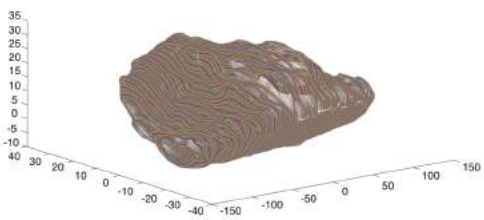

Fig. 7. Slices of the sedimentation.

The slice is obtained by intersecting the scanned object with several planes, and then each slice with several lines, the result was stored in a matrix. Through this matrix we obtain Figure 8 that represents the caliper thickness of the fertilizer sediment. Each pixel is the distance between the lowest and the highest point in the model at that mapped point in the x-y plane.

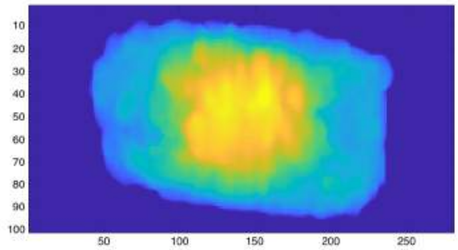

Fig. 8. Thickness plot of the fertilizer sediment

To generate the dataset we considered a patch of the original thermal image, to get the intensity of all thermal pixels in the window. For the thickness image of the fertilizer sediment we used the same patch but considered only the central pixel of the patch. Different sizes of patches can be used. In this work we have 3x3 and 5x5 patches composing our dataset. The data are normalised and then applied in the neural network

4.4 A model to map thermal images to deposit profile

Our goal is to have a deposit model from the thermal non invasive images. For this experience we proposed to use a neural network to learn the mapping between each pixel of the thermal image $I^T(a,b)$ into a deposit profile $I^D(a,b)$. We considered a patch of the original thermal image to train the NN, see Figure 2.

We use a multilayer perceptron NNs. The network has n^2 neurons in the input layer (associated with a nxn mask), one hidden layer with 25 neurons and one neuron in the output layer, for the dataset generated sliding a non mask. The hidden layers have relu activation functions. The output neuron is a linear neuron. We have used Adam optimization algorithm to update connection weights.

5. TESTS AND RESULTS

To validate our proposal we have developed our scaled dataset. After we train the NN with the dataset.

5.1 The Setup and the Dataset

Our approach consider that a NN can learn a scaled dataset to map thermal image to deposit profile. We have developed a scaled mockup of a steel a pipe with 400 mm of length, 75 mm of external diameter and a 2 mm wall thickness, a wooden frame for support the pipe at each end, an adjustable heat gun at one side and an air extractor at the other. The idea behind it being that several different scenarios could be set up, by adjusting the temperature, flow rate and distribution of dust piles inside the duct.

The Infrared Thermography is made by a Thermoteknix 307k thermal camera. It captures monochromatic heat signatures at 640x480 pixel resolution. It also has Non Uniformity Compensation (NUC), a feature that enables self-calibration on account of small variations between neighboring pixels, which is normal for devices of this type Vollmer and Mollmann (2018). The component that captures the image inside the camera is not a Charged Coupled Device (CCD), but instead a Microbolometer array that is made up of amorphous silicon and vanadium oxide elements. Those are affected by electromagnetic radiation of wavelengths between 7.5 and 14 micrometers, changing their internal resistance and thus composing the thermal image Vollmer and Mollmann (2018).

This system differs from Mercury Cadmium Telluride (MCT) sensors, in the fact that it doesn't have to be cryogenically cooled Vollmer (2018).

The images are organized following a standard and stored in a non-compressed format to avoid loss of data. File names include information such as the ambient temperature, timestamp and indications of which type of obstruction is being tested.

To start the imaging procedure, the distance between the camera lens and the model is set at 800 mm, the heater at 120^oC, and fan input voltage at 12V. The camera scale is fixed at 40^oC minimum and 135^oC maximum and its color palette set to grayscale. If necessary, the temperature scale can be readjusted, being careful to compensate for it on pre processing. Then, a period of 60 minutes is required for stabilization of the thermal process. This can be checked with the capture of a thermal image every 20 minutes. If the difference between them is only the noise, the model is considered stable. It is important to trigger the camera self-calibration routine before capturing any image, to ensure consistency due to the non-uniformity factor.

After that, the heater and fan are briefly turned off, to allow access to the interior of the pipe. The first obstruction to be loaded is a distribution of 250g of Nitrogen Phosphorus Potassium (NPK) type fertilizer on the bottom of the duct, as per Figure 9.

Fig. 9. Fertilizer on the bottom of the duct

The devices are turned on again for 60 more minutes. The stabilization of the system is checked, and then another image is captured and labeled accordingly. When this process is completed, the data can be analyzed.

The next step is to scan the fertilizer rock that has settled with the heat present in duct scale model. The scanning is made by pointing the SenseTM 3D laser scanner to the sedimentation and rotating it in a 360^o spin around the object, scanning all faces of the fertilizer sediment.

Processing of the images is realized in a numerical computing environment, such as MATLAB Solomon and Breckon (2011b). This procedure consists of the subtraction of different sets of thermal images, in pairs, resulting in diagrams and 3D representations of the gradient change in temperature of a surface.

5.2 *The Training of NN*

We have used X samples to train our NN. Each sample is a nXn matrix which is a mask nXn centered in (x, y) position of the original thermal image. The sample has as label the Z_{height} obtained from 3D laser measure to this area.

The data was divided in an 80/20 configuration, for the training and test sets respectively. After 10000 epochs we got the predicted and measured results, as in Figures 10 and 11. The implementation of the neural network was made in Spyder scientific development environment.

The root-mean-square error (RMSE), equation 1, was chosen to evaluate the performance of the model for the dataset, n, that is being analyzed. The RMSE calculates the quadratic mean of the differences between measured values and predicted values.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Measured_i - Predicted_i)^2}. \qquad (1)$$

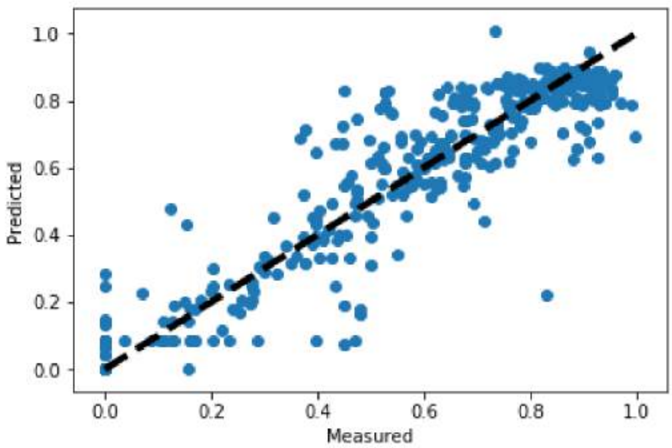

Fig. 10. Mapping when sliding a 3x3 window.

The results obtained in both models are applied in the RMSE equation. For the mapping model that considers sliding a 3x3 mask, we got a RMSE of 0.11. And a standard deviation of 0.28. For the model that considers a 5x5 mask, a 0.20 RMSE was obtained. And a standard deviation of 0.20. The model has good results since a 0 RMSE value indicates a perfect fit to the dataset.

6. CONCLUSION

The present work showed a non invasive method to identify dust sedimentation inside ducts of fertilizer industry.

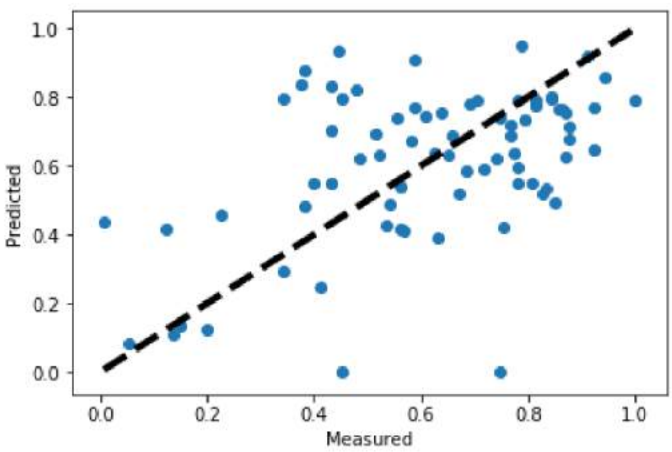

Fig. 11. Mapping when sliding a 5x5 window.

We proposed a NN to model the deposit profile using thermal non invasive images and 3D scanner associated with a scaled mockup dataset.

A scale model was developed in a controlled environment and determine parameters for the real case application in a big fertilizer company located in the southern part of Brazil.

The multilayer perceptron neural network learned the mapping between each thermal pixel into a deposit profile and obtained some good results, showing that it is possible to detect the sedimentation that is occurring inside the duct from a thermal image.

As future work we aim to extend our dataset to other fertilizer distribution profiles. As well as to evaluate in detail the effect of scaled trainned NN in real scenarios.

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