Thermographic Non-Invasive Inspection Modelling of Fertilizer Pipelines Using Neural Networks

Marta Duarte*, Victor Coch*, Jovania Dias*, Silvia Botelho*, Nelson Duarte* and Paulo Drews Jr.*
*Federal University of Rio Grande (FURG)
*Computer Science Center - C3 , Rio Grande, Brazil
Email: marta.anjosduarte@gmail.com

***Abstract*—Industry pipeline fault, like blockage can create major problems for engineers and financial loss for the company. The blockage detection is necessary for smooth functioning of an industry and safety of the environment. This work presents a model for non-invasive inspection of pipes. It proposes the use of a neural network to identify the obstruction stage in fertilizer industry, using external thermal images obtained from the pipelines. A dataset capable of mapping the external thermal behavior in profile of the internal deposit is developed. The Multilayer Perceptron neural network was able to learn the thermal pixel mapping in a deposit profile, obtaining satisfactory results.**

I. 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 growing world population has been responsible for the increase in the demand for food. The International Fertilizer Industry Association (IFA) mentions that soil fertility is a major point in this context as it is necessary to replenish nutrients removed from the soil through plantations. The three main nutrients are nitrogen (N), phosphorus (P) and potassium (K), they are key to increasing food production [1].

The fertilizer industry demands not only more better quality, but also productivity and customized solutions. To approach these needs, technological advances in software and hardware bring greater capabilities to operations, smart factories or Industry 4.0 are focused on integrating technologies to promote increased productivity and operational efficiency [2].

The production of fertilizers takes place in basically three stages: production of raw and basic materials, basic fertilizers and mixtures, this last stage is responsible for mixing the basic fertilizers nitrogen (N), phosphorus (P) and potassium (K) according to the particular requirements of the soil, composing the bulk blend fertilizers [3]. 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.

Manual periodic cleaning is necessary to unblock the duct, which causes the whole production to stop. The total stop of the factory leads to a significant loss in the company's profits. The cleasing maintenance of pipelines is of great importance to keep the flow 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 scaled pipe mockup is used to simulate different obstruction patterns. A thermal camera is used 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). A scaled model was 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.

Thermography is a non-destructive and non-invasive 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 [4], [5], [6]. 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, [6]. In this work two of these technologies are used, thermal camera and 3D laser scanner.

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

The paper is organized as follows. Section II is a brief about visual computing and artificial neural networks. Section III introduces the methodology where NN algorithms are development to map thermal images to depot profile. Section IV presents the proposed dataset. Section V a discussion of obtained results is presented. The conclusions are introduced in Section VI.

II. Visual Computing and Artificial Neural Networks

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 [5].

For the future of production, academics and professionals anticipate significant efficiencies mainly through the consequent digital and intelligent integration of manufacturing processes [7].

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 achieve industry 4.0 [6], this technology involves capturing, analyzing, and synthesizing visual data through computational technology [5], including techniques for computer graphics, such as real-world object modeling and simulation, human-machine interaction, image processing, and more [6].

A. Thermography

Thermography is a technique for obtaining images in which the infrared spectrum is adopted to measure the heat emitted by an object [8]. 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 [9]. 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 [10].

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 [11]. 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.

B. The 3D Laser Scanner.

A 3D laser scanner is a device capable of analyzing objects or environments in the real world and collect data about their shape and even their color. With the data collected it is possible to build three-dimensional digital models [12], [13]

A laser stripe is projected onto a surface and the reflected beam is detected by CCD (Charged Coupled Device) 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 [12].

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 [13].

C. 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 [14]. 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 repeatedly presented with the training data and the weights in the network are adjusted until the desired mapping is found [14]. The goal is to find the combination of weights which result in the smallest error value. The most common learning is the backpropagation algorithm.

The backpropagation [15] algorithm is widely used to adjust synaptic weights to minimize the error between the desired and actual outputs. The backpropagation algorithm seeks for the minimum global error by propagating the error signal back through the network and then adjusting the weights to minimize the error [14], [16].

III. METHODOLOGY

This work proposes a non-invasive method based on computer vision to infer the degree of pipe obstruction in fertilizer industries. An overview of the method can be seen in Figure 1.

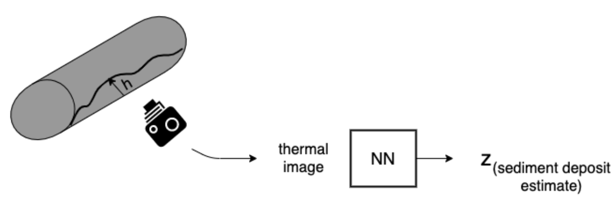


Fig. 1: Overview of the proposed method to infer the degree of obstruction in pipes.

The idea is to use a thermal camera that acquires images associated with the temperature emitted by the external surface of the pipe. This image will be processed by a neural network that will provide the normal deposit height with the curvature of the pipe section. The proposal uses neural networks to map thermal images in deposit profiles. The idea is to use a neural network to map the relationship between the pixels of the thermal image obtained from the outside of the tube and the sediment profile inside.

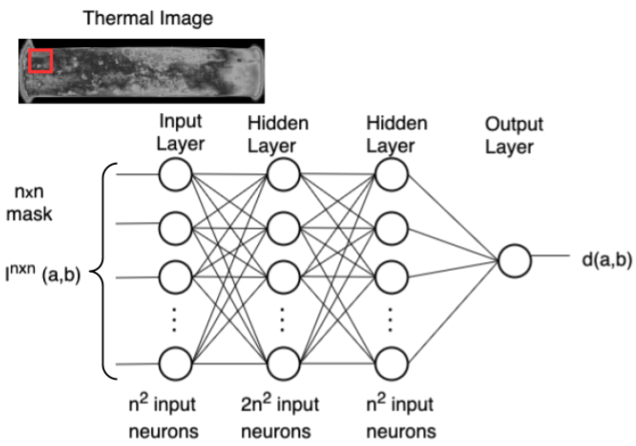


Fig. 2: Proposed neural network for mapping the thermal behavior in the deposit profile.

The hypothesis adopted is that the fertilizer is a less thermochemical material than the steel of the pipe and the air inside it. Which makes it possible to capture in the image the accumulation of sediment from the thermal behavior of the outside of the duct.

It is possible to observe in the Figure 4b that the temperature of the tube decreased with the addition of sedimented material, which leads to the perception that the fertilizer acts as a thermal barrier. This indicates that when the temperature in the duct decreases, an undesirable accumulation of sediment is occurring. And this can lead to an adverse situation to the point of affecting the entire operation of the production of fertilizers.

Due to the complexity of an analytical model that describes the nonlinearities of this phenomenon, AI techniques are used to learn complex mapping relations from data [16]. Thus, to map the thermal image at the obstruction level it is decided to use a Multilayer Perceptron (MLP) neural network due to the small amout of data available. A MLP requires smaller number of parameters for a good generalization when compared to a CNN (Convolutional Neural Network) that are more complex and requires a bigger number of parameters and data samples for a good performance [17], [18].

The MLP network will analyze the image in small windows of $n_X n$ pixels (input) providing the deposit profile associated with the center (a, b) of the window (output). Figure 2 presents the architecture of the neural network used. The network has an input layer with n^2 neurons ($n_X n$ mask), a hidden layer and an output layer with a scalar neuron (height z of the deposit profile).

That said, it becomes necessary to build a dataset to train the network. Obtaining such an accurate dataset, in situ, is not a simple task. This difficulty is due to the fact that the interior of the duct presents a highly inhospitable environment for measuring equipment. The large flow of dust and the high temperatures make it impossible to obtain an adequate ground truth of the deposit. To contour this difficult, it is proposed to adopt a dataset obtained in a controlled experiment. A scale model of the tube is then used. Possible sediment deposition models capable of defining the ground truth are manually elaborated and their shapes and dimensions are obtained with a 3D laser scanner. These models are installed inside the model duct. Hot air flows are forced inside the model tube and the temperatures that occur outside are captured by a thermographic camera. With the data obtained in these experiments, the desired ground truth is then built. This procedure is further detailed in the section that follows.

IV. 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).

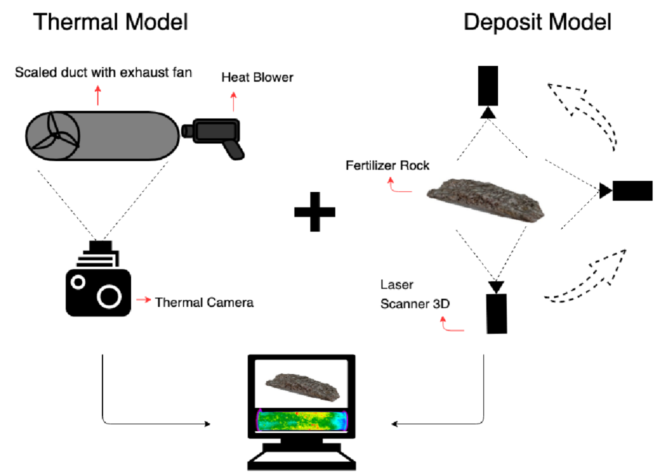


Fig. 3: Proposed method solution.

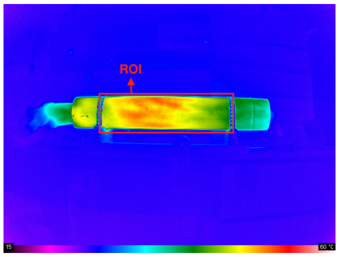
A. *Dataset Input: The Thermal Image*

The thermal image is obtained by pointing the thermographic camera towards the scale duct, which has a thermal blower and an exhaust fan installed in it. The necessary processing is then performed in the region of interest (ROI) of the thermal image obtained from the outside of the pipeline under study. In this way, the thermal behavior of the exterior of the model duct is obtained under typical operating conditions of the real duct.

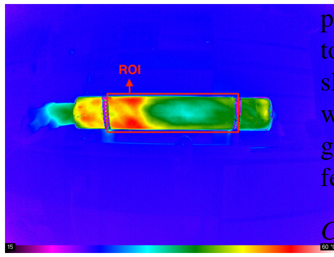
Figure 4a shows an example of an infrared thermography image of the duct scale model when it was empty. While Figure 4b is the same duct but with fertilizer sediment inside the pipe.

B. *Dataset Label: the deposit profile*

Sedimentation of the fertilizer occurs at the bottom of the tube, in horizontal tubes. The deposit profile $z(x, y)$ is obtained with a handheld 3D laser scanner. A view of the scanned profile is shown in Figure 5. With the scanned object it is possible to obtain the dimensions of the stone and associate each position of the thermal image in a deposit profile.



(a) Empty pipe.



(b) Obstructed pipe,

Fig. 4: Examples of thermal images obtained in the experiment.

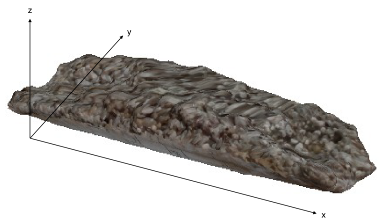
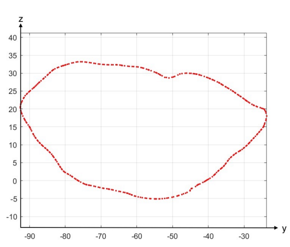


Fig. 5: The fertilizer sedimentation.

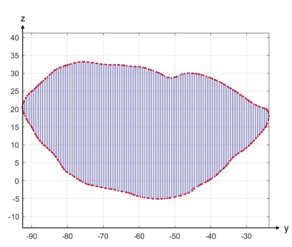
The result of the accumulation scan is a file exported from the 3D scanner's own software. The output file is a data structure containing a list of vertices and a list of faces of the object. Each vertex is a point in three-dimensional space and each face is a triangle formed by three points, that is, the scanned surface is formed by polygons. The vertices are (x, y, z) coordinates and the faces are lists of three vertices each.

Transverse slices are made along the length of the object, the slices are intersections of planes with the 3D object. Each intersection results in sets of points that form a polygon and each polygon corresponds to a 2D slice of the deposit model. Figure 6a shows an example of a slice made on the scanned object.

The heights of the slices are measured by the intersection of vertical lines along the width of the object with the polygon that forms the slice, Figure 6b. Each intersection results in a pair of points. The distance between these points corresponds to the height of the accumulation at a given point on the slice. The calculated heights are stored in a vector associated with each slice. The final image of the deposit model is then generated where the point x, y represents the thickness of the fertilizer.



(a) Example of a 2D slice obtained..



(b) Intersection of vertical

Fig. 6: Example of a slice made in the object to obtain the measures, the red dots correspond to vertices which belong to the object and are being intercepted by the plane that corresponds to the slice.

C. Association of Thermal Images with Deposit Profile

To generate the dataset, a fragment of the original thermal image is considered in order to obtain the intensity of the thermal pixels in the window. Two different approaches of obtaining the obstruction level are used. In the first the intensity of the thermal pixels in the window is used as input to the NN. And in the second, besides the intensity of the thermal pixel, the height in which the patch is being slid in the thermal image is also used to feed to the input of the MLP. This second alternative explicitly incorporates into the network structure the thickness distinction resulting from measuring a specific region of the pipe. Thus, it is expected with this supplementary information to decrease the complexity of mapping the network.

For the thickness image of the fertilizer sediment the same window is used but considering only the central pixel of the patch. Different window sizes can be used. In this work, 3x3 and 5x5 windows are used to compose the dataset. The data are normalised and then applied in the neural network.

D. A model to map thermal images to deposit profile

The ultimate goal is to develop a deposit model using non-invasive thermal images. For this, it is proposed to use neural networks that learn the association between the pixels of the thermal image $I^T(a, b)$ and the deposit profile $z(a, b)$. It is considered to run a patch over the thermal image in order to acquire data to train the neural network, as shown in Figure 2.

The neural network used is a Multilayer Perceptron. The network architecture has an input layer with n^2 neurons, a hidden layer with $2n^2$ neurons and 1 neuron in the output layer. The ReLu activation function is used in all layers. The optimization algorithm Adam [19] is used to adjust the weights of the network in order to minimize the error function.

V. Results

To validate the proposed methodology a scaled dataset was developed. The neural network is trained with this dataset.

A. The Setup and the Dataset

The approach considers that a NN can learn a scaled dataset to map thermal image to deposit profile. A scaled mockup of a steel pipe was developed. It contains 600 mm of length, 100 mm of external diameter and a 0,43 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 is 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 [20]. 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 [20].

To start the imaging procedure, the distance between the camera lens and the model is set at 800 mm, the heater at 100^oC, and fan input voltage at 12V. The camera scale is fixed at 25^oC minimum and 55^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.

The fertilizer grains of the NPK type (Nitrogen, Phosphorus and Potassium) are added inside the scaled duct so they can agglutinate with heat and form the deposit. The heat blower is then turned on for approximately 60 minutes to capture the thermal image of the duct with the fertilizer sediment. The experiment stabilization is verified and the new image is captured and annotated. The data is analyzed when the entire process is completed.

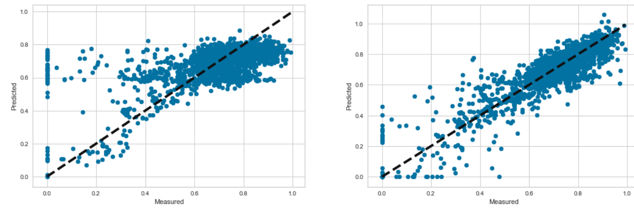
The next step is to scan the fertilizer rock that has settled with the heat present in duct scale model. The scanning is made by pointing the SenseTM 3D laser scanner to the sedimentation and rotating it in a 360^o spin around the object, scanning all faces of the fertilizer sediment.

Processing of the images and the scanned object is realized in a numerical computing environment, such as MATLAB [21].

B. The Training of NN

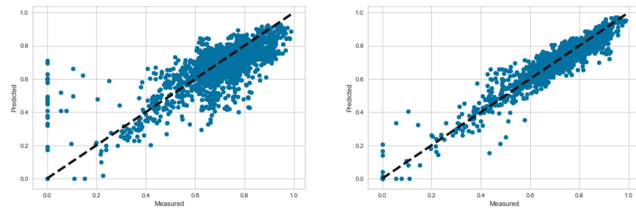
Each sample corresponds to an nxn window containing the intensity of the pixels (3x3 and 5x5 size windows were used). The window slides through the thermal image. The sample label (Z_{height}) is the central pixel of the same $n_X n$ size mask obtained from the laser scanner measure of the same area. When considering a 3x3 window 8799 samples were obtained to train the NN. And when considering a 5x5 window 8365 samples were used to train the neural network.

The data was divided in an 80/20 configuration, for the training and test sets respectively. The predicted and measured results are obtained after 1000 epochs, as in Figures 7a, 7b, 8a and 8b. The implementation of the NN was made in Spyder scientific development environment, using Python and libraries such as Keras, Pandas and Scikit-learn.



(a) Results obtained using the intensity of the thermal pixel as input for the NN.
(b) Results obtained using the intensity of the pixel and the height at which the.

Fig. 7: Mapping results obtained when sliding a 3x3 window.



(a) Results obtained using the intensity of the thermal pixel as input for the NN.
(b) Results obtained using the intensity of the pixel and the height at which the.

Fig. 8: Mapping results obtained when sliding a 5x5 window.

In the graphs of Figures 7b and 8b, it is possible to observe a smaller dispersion of the data, in relation to the graphs of Figures 7a and 8a. The closer the data points to the regression line, the more suitable the model is.

The root-mean-square error (RMSE) Eq. 1, and the mean-absolute-error (MAE) Eq. 2 were chosen to evaluate the performance of the model. The RMSE calculates the quadratic mean of the differences between measured values and predicted values. The mean absolute error represents the mean deviation between measured and predicted values. The coefficient of determination, R^2, is the proportion of the variance in the dependent variable that is explained by the linear model. The R^2 ranges from 0 to 1, the closer the value of R^2 is to 1 the better the model fits the data. For RMSE and MAE lower values indicates better fit to the dataset.

The results obtained can be observed in Tables I and II.

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

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|Measured_i - Predicted_i\right|. \quad (2)$$

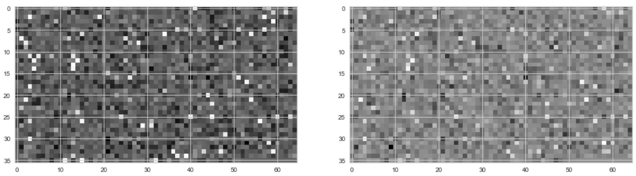
TABLE I: Results obtained using a 3x3 window.

Input	RMSE	MAE	R^2
Thermal pixel intensity + height	0.09	0.06	0.6
Thermal pixel intensity	0.14	0.09	0.3

The residual is the difference between the true measured value and the one predicted by the neural network. Residuals

TABLE II: Results obtained using a 5x5 window.

Input	RMSE	MAE	R^2
Thermal pixel intensity + height	0.04	0.03	0.9
Thermal pixel intensity	0.10	0.06	0.4



(a) Thermal pixel intensity as input. (b) Thermal pixel and height as input.

Fig. 9: Residual color map obtained when considering a 3x3 window size.

represent the part of the target value that the model cannot predict. Residual color maps and histogram of residual are a way to analyze the residual behavior and the performance of the model.

Figures 9a, 9b, 10a and 10b represent color maps of the residuals in shades of gray. The results are relative to the test set of the model used. Larger residues are represented in darker tones. The absence of dark spots indicates that there are no areas that the neural network had any problem to learn.

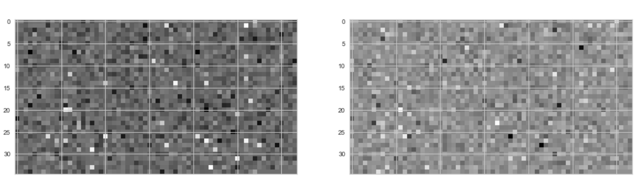
As for the histogram of residuals when symmetric bell-shaped and centered at zero indicates that the model makes mistakes in a random manner. If the residuals do not form a zero-centered bell shape, there is some structure in the model's prediction error. A positive residual indicates that the model is underestimating the target (the actual target is larger than the predicted target). A negative residual indicates an overestimation (the actual target is smaller than the predicted target).

The model showed good results that can be observed in Figures 11a, 11b, 12a and 12b. All histograms of residuals obtained are bell-shaped and distributed around 0.

Using not only the intensity of the pixel, but also the height at which the patch is being extracted as input for the neural network brings better results to the model, as more information is added, thus removing possible ambiguities in the data.

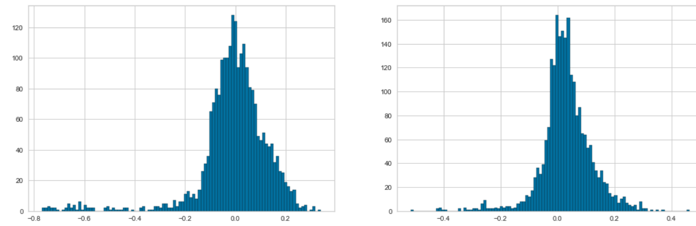
VI. CONCLUSION

The work presents a model for non-invasive inspection of pipes, using a thermal camera, 3D laser scanner and neural networks. The model is capable to identify the stage of obstruction in fertilizer industry ducts.



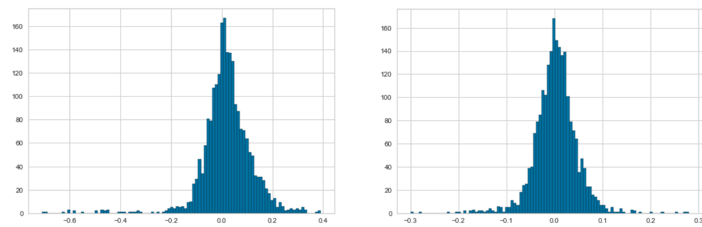
(a) Thermal pixel intensity as input. (b) Thermal pixel and height as input

Fig. 10: Residual color map obtained when considering a 5x5 window size.



(a) Thermal pixel intensity as input for the NN. (b) Thermal pixel and height as input.

Fig. 11: Histogram of residuals when considering a 3x3 window size.



(a) Thermal pixel intensity as input for the NN. (b) Thermal pixel and height as input.

Fig. 12: Histogram of residuals when considering a 5x5 window size.

A neural network is proposed 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 determines parameters for the real case application in a big fertilizer company.

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

Adding more variables to the model might help the model capture the patterns that are not captured by the current model. The use of the pixel intensity together with the value of the height at which the window is in the thermal image brought better results for the mapping, as it removes possible ambiguities that the dataset may contain.

Future work aims to extend the dataset to other fertilizer distribution profiles, as well as to evaluate in detail the effect of scaled trainned NN in real scenarios.

REFERENCES

[1] H. F. Reetz, *Fertilizers and their efficient use*, 2016.

[2] M. Saunila, M. Nasiri, J. Ukko, and T. Rantala, "Smart technologies and corporate sustainability: The mediation effect of corporate sustainability strategy," *Computers in Industry*, vol. 108, pp. 178 – 185, 2019.

[3] O. Miserque and E. Pirard, "Segregation of the bulk blend fertilizers," *Chemometrics and intelligent laboratory systems*, vol. 74, no. 1, pp. 215–224, 2004.

[4] A. Moreno, G. Velez, A. Ardanza, I. Barandiaran, Á. R. de Infante, and R. Chopitea, "Virtualisation process of a sheet metal punching machine within the industry 4.0 vision," *International Journal on Interactive Design and Manufacturing (IJIDeM)*, vol. 11, no. 2, pp. 365–373, 2017.

[5] J. Posada, C. Toro, I. Barandiaran, D. Oyarzun, D. Stricker, R. De Amicis, E. B. Pinto, P. Eisert, J. Döllner, and I. Vallarino, "Visual computing as a key enabling technology for industrie 4.0 and industrial internet," *IEEE computer graphics and applications*, vol. 35, no. 2, pp. 26–40, 2015.

[6] A. Stork, "Visual computing challenges of advanced manufacturing and industrie 4.0 [guest editors' introduction]," *IEEE computer graphics and applications*, vol. 35, no. 2, pp. 21–25, 2015.

[7] J. Zhou, "Digitalization and intelligentization of manufacturing industry," *Advances in Manufacturing*, vol. 1, no. 1, pp. 1–7, Mar 2013.

[8] C.-Y. Chen, C.-H. Yeh, B. R. Chang, and J.-M. Pan, "3d reconstruction from ir thermal images and reprojective evaluations," *Mathematical Problems in Engineering*, vol. 2015, 2015.

[9] L. Acampora, F. De Filippis, A. Martucci, and L. Sorgi, "3d reconstruction of thermal images," in *Proceedings of 26th Aerospace Testing Seminar, Los Angeles (USA)*, 2011.

[10] H. G. Zadeh, J. Haddadnia, O. R. Seryasat, and S. M. M. Isfahani, "Segmenting breast cancerous regions in thermal images using fuzzy active contours," *EXCLI journal*, vol. 15, p. 532, 2016.

[11] R. Osornio-Rios, J. Antonino-Daviu, and R. Romero-Troncoso, "Recent industrial applications of infrared thermography: A review," *IEEE Transactions on Industrial Informatics*, vol. PP, pp. 1–1, 12 2018.

[12] S. Son, H. Park, and K. H. Lee, "Automated laser scanning system for reverse engineering and inspection," *International Journal of Machine Tools and Manufacture*, vol. 42, no. 8, pp. 889–897, 2002.

[13] M. Ebrahim, *3D laser scanners: History, applications, and future*. LAP LAMBERT Academic Publishing, 2016.

[14] M. W. Gardner and S. Dorling, "Artificial neural networks (the multilayer perceptron)—a review of applications in the atmospheric sciences," *Atmospheric environment*, vol. 32, no. 14-15, pp. 2627–2636, 1998.

[15] D. E. Rumelhart, G. E. Hinton, and R. J. Williams, "Learning representations by back-propagating errors," *nature*, vol. 323, no. 6088, pp. 533–536, 1986.

[16] S. Haykin, *Redes neurais: princípios e prática*. Bookman Editora, 2007.

[17] K. Sato, C. Young, and D. Patterson, "An in-depth look at google's first tensor processing unit (tpu)," *Google Cloud Big Data and Machine Learning Blog*, vol. 12, 2017.

[18] N. O'Mahony, S. Campbell, A. Carvalho, S. Harapanahalli, G. V. Hernandez, L. Krpalkova, D. Riordan, and J. Walsh, "Deep learning vs. traditional computer vision," in *Science and Information Conference*. Springer, 2019, pp. 128–144.

[19] D. P. Kingma and J. Ba, "Adam: A method for stochastic optimization," *arXiv preprint arXiv:1412.6980*, 2014.

[20] M. Vollmer, *Infrared Thermal Imaging: Fundamentals, Research And Applications*. Wiley-vch, 2018.

[21] C. Solomon and T. Breckon, *Fundamentals of Digital Image Processing: A practical approach with examples in Matlab*. John Wiley & Sons, 2011.