Intelligent Manufacturing of Polyurethane foam accomplishing surface inspection by Image Processing and Artificial Neural Networks techniques

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Abstract

Machine vision is becoming one of the more efficient emerging technologies for the fast and reliable control of different types of products. This technology allows obtaining a big amount of information, superficial and dimensional, of the pieces at high speed. The objective of the present article is to show a successful machine vision application in an industrial sector where this technology is hardly introduced. Quality assurance is a necessity in the industrial processes. Some of these processes are automatized; otherwise, there are still many tasks that are accomplished manually and subjectively by an expert, such as these quality control tasks. The use of this manual control limits a lot the reliability and repetitivity of the results, since the human performance is not constant along the whole working day, and not only the localization of the defect but also its magnitude are relative depending on the person in charge of the identification. The automatization of the processes solves these limitations. This happens in the manufacturing process of polyurethane foam. This is a long process throughout two days from the initial moment of pouring the component chemical substances in the mould designed for that, till obtaining the foam block in its final shape. There are some quantifiable parameters to guarantee the quality of the product, such as the hardness, permeability or number of pores per centimeter of the foam, but these are not obtained till the end of the process, and an expert in the foaming cycle only knows them. Inadequate proportions of the chemical constituents in the origin are detected in the end, when there is no possible solution, with the consequent economic loss for the company. Therefore, it is important to be capable of predicting which will be the final result from the earlier stage of the process. So, knowing the evolution of the process, the production variables can be immediately changed if needed. The selected parameter to focus the aim of the project presented in this article, is the number of pores per centimeter calculated over a small sample of foam. As result from the project, a machine vision system has been accomplished and placed in the first stage of the foaming machine. This system includes the expert knowledge, but in a more reliable and repetitive way. It carries out three main block tasks: 1. Acquisition of an image of a foam sample;2. Processing of this image by classical algorithm methods (morphologic, filters) to obtain output values (histogram, initial number of pores); 3.Introduction of the results of the previous phase in an artificial intelligence system based on neural networks. The output of this last will provide with the estimated number of pores that the foam will present in the end. This value will indicate the person in charge of supervision to know what to do next. The results achieved in this first approach are really promising and augur the chance of automatizing the system in the industrial plant.

1. Introduction

The polyurethane foam is a material used in different industrial sectors, such as automotive, shoes, household goods, and furniture. To satisfy the necessities of quality of these sectors, the manufacturing of foam requires certain specific controls throughout the process. One of the main parameters to establish the mechanical characteristics of this product is the number of pores per centimeter that the external coat of the foam has at the end of the foaming process. Besides, this parameter is an indirect way of knowledge of other parameters (hardness,

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permeability). The number of pores per centimeter depends on the percentage of components of the mixture and the value of some variables (temperature, pressure) in the chemical process. The variation of these variables will cause the higher or smaller hardness, and the higher or smaller pore density, among others.

To make sure that the right number of pores per centimetre will be got, a process expert "foamer" controls the foam in the first steps of the process. Otherwise, the real information about the characteristics of the pore is not obtained till the foam is "cured", about 48 hours after having started the foaming process. The "foamer" uses indirect visual methods to try to estimate the final characteristics of the foam. Due to the fact that this observation is subjective and indirect, it has its limitations. Besides, the company depends on one or two experts in this process. One of the company's aims is to make the detection of errors in the foam faster, usually detected two days later at the laboratory.

The necessity of bringing in a new technology arises in order to guarantee the obtaining of these values in a reliable and repetitive way. The machine vision technology is revealed as a valid option.

2. Problem formulation

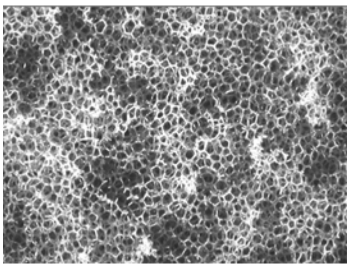
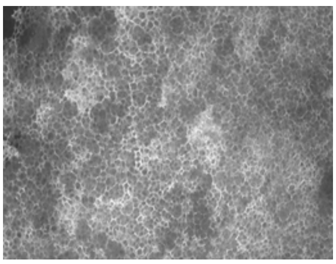
The objective of the process is to estimate the number of pores per centimeter that the foam will have in the end of the foaming process, two days after the inspection.

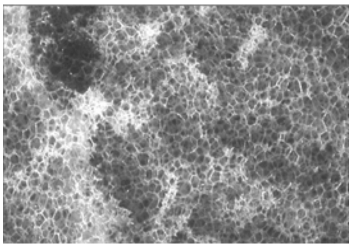
The problem to solve is to obtain the characteristics of a sample acquired on-line at first stage of the production by image processing techniques and to transform that information into that one that would be attained at the end of the process, off-line at the laboratory. Therefore, it is necessary to interpret those obtained values in the first steps of the foaming process and associate them with the final characteristics of the foam once it has completed its manufacturing cycle. Both parts have their own difficulty. The obtaining of a good image that enhances the pores characteristics will be essential, and in spite of using a good lighting, the irregularity, break or low definition of the outline of the pore makes the computational processing difficult.

It is also necessary to connect values in different stages of the process that do not have any mathematical link and even they can lead to different output values with the same input data according to the features of the foam (model, color). The challenge is to know the output of a non-linear system generated by the chemical reactions among all the components. The only available information is the one provided by the foaming process expert.

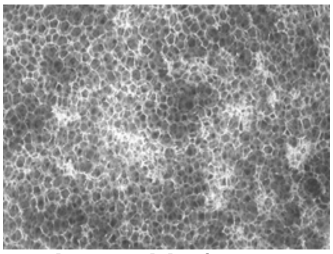
This application is brand new, references of similar applications to this sector have not been found. Nowadays, the control is accomplished in the laboratories once the foam has ended its process but no preventive method has been identified.

There is a quite big range of foams, according to the color or the shape and size of the pore. As a sample, here they are four different types of foam:

	
Sample 1. Model S28	Sample 2. Model s40bpd



Sample 3. Model Sh60



Sample 4. Model srf

Figure 1. Images of 4 different models of foam

As it can be seen, every foam is different: the color is gray or dark, the size of the pores is different, and the internal structure is completely different although it cannot be appreciated in these pictures. It can also be noticed the difficulty in finding the upper layer, since the second and third and even more sound layers can be seen.

3. PROBLEM SOLUTION

The whole solution has been divided in two big blocks:

1) conventional image processing
2) new algorithm development with techniques for the representation of non-lineal systems.

Before that, it is necessary to design the vision system. The choice of the elements and their proper arrangement is fundamental for the obtaining of good quality images.

The system includes mechanical, electric, machine vision and software development. The mechanical system is a metallic frame with a structure inside that keeps the elements in fixed distances and isolates the sample from the external light and environmental attacks. It is constituted by:

- An input platform (today the sample is introduced manually) and support of the obtained sample of the foam at a fixed distance.
- A support portico for the suspended camera over the foam sample.
- A variable mechanical element for keeping the lighting at a stable distance.

This is the overview of the whole system:

Figure 2. System overview

3.1.1 IMAGE ACQUISITION SYSTEM

The main components of the image acquisition system are the following ones:

- Camera: Black and white IEEE1394 camera, 640 x 480. Although it is not a big resolution, it is enough for this application, having in mind that the field of view is 12 mm,. The camera offers an auto adjustable feature of brightness and contrast, very useful since the chromatic characteristics of the foam are changeable.
- Dedicated illumination system: in a machine vision application, the lighting system is very important. It can be up to the 30% of success. The illumination chosen method is a "Darkfield" type [6] with red LEDs. This layout of the LEDs in a circular element is specially indicated for those applications in which the enhancement of borders is needed or the contrast improvement is required in surfaces where this is difficult to obtain by the use of other lighting methods. The isolation from external light is important.

In industrial environments the electromagnetic interferences are habitual. It is advisable to prevent from these. It has been chosen the communication protocol 1394 to avoid this alteration by noise in the reception of the images.

3.1.2 PROCESSING SOFTWARE.

The programming environment is NI LabWindows CVI, image processing libraries NI-IMAQ vision and MvTec HALCON, NI-IMAQ control software for the communication protocol IEEE1394 and Matlab for neural networks design. It has been developed a processing algorithm that consists of 3 levels: morphologic, statistical and neural analysis, since the classical image processing cannot itself solve the application.

3.1.2.1. MORPHOLOGICAL PROCESSING

Once the image is obtained, conventional processing algorithms are applied [3]: Auto threshold algorithm, enhancing filters, masks, so that a first approach to the characteristics of the foam are obtained. The regions in the images that do not provide information are removed. A sample of sequence of operation is shown underneath:

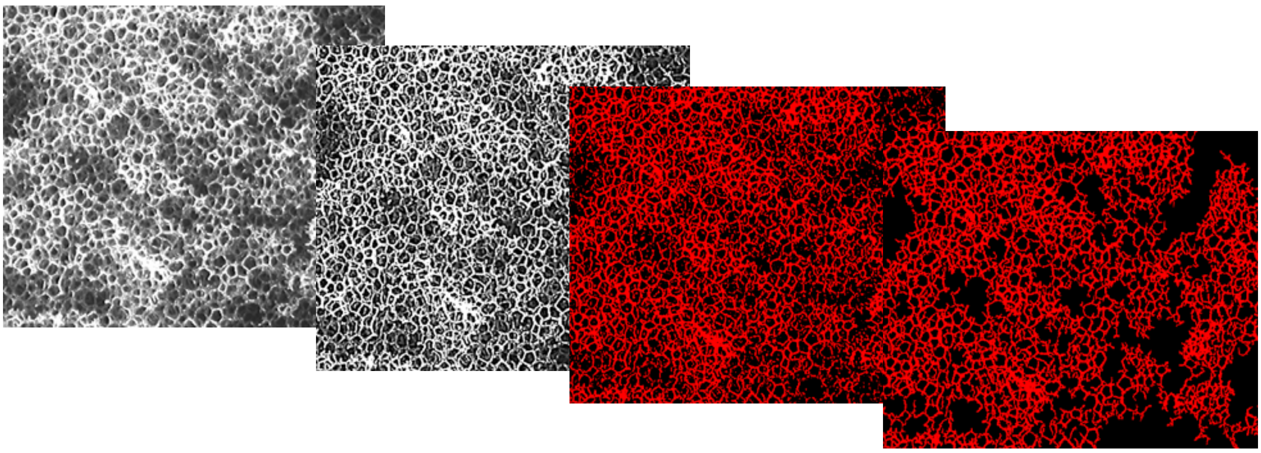


Figure 3. Morphological analysis sequence (Enhancing filters, Auto threshold algorithm, and masks)

3.2.2 STATISTICAL PROCESSING

From the morphological processing result on, different methods have been evaluated for the obtaining of the number of pores. But the foam is not still cured in the moment of inspection and the pore presents discontinuities, the superposition of different layers of pores and the low definition of their limits. This all originates processing difficulties. Finally, it has been chosen a method that reproduces the counting way of the foaming experts: row transition counting, but processing all the rows whereas only 3 rows are evaluated at laboratory.

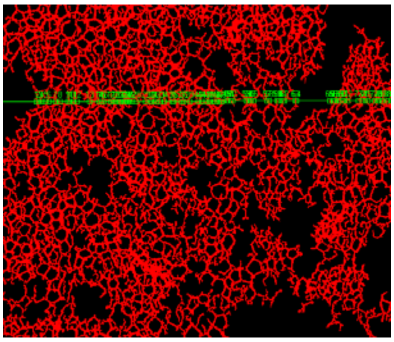


Figure 4. Transition counting

This transition counting allows the obtaining of a redundant value in each of the 480 lines in the image. With easy statistical methods, some extreme counting values in the Gauss bell and those that do not have reached an established threshold value for the available information [4] are removed. With those ones that have this admissible value, an average calculus is made and it is related with a previous gauging of the field of view and the unit of surface. In this way, the first useful value is obtained: number of pores per centimeter in that initial moment of the foaming chemical process. It is necessary to remark that this number is very different to that one obtained for the same foam at the laboratory, since they are obtained at different stages of the process, with a time different of 48 hours.

3.2.3 NEURAL ANALYSIS

The value that must be the output of our system is the number of pores per centimeter that foam will have at the end of the foaming process. The initial available value is the number of pores per centimeter obtained in the initial stage of the process. What we are looking for is the laboratory number of pores, radically different. How can these two values be connected? How can this non-lineal system be simulated? It is needed to associate an output to each input. [1,2,5]

It is necessary to "learn" how many final real pores correspond to certain characteristics of the initial number of pores according to the model of foam, the color and other characteristics. To solve this last point, it was thought to use Artificial Neural Networks. One of the more powerful aspects of the neural networks is that they allow simulating the behavior of non-linear systems without having to find a mathematical model that describes them. Simply, they "learn" the behavior.

In this way, once the network has been designed and developed, it will be trained, by providing a wide range of filtered data got from the images (initial value) and the real number of final pores (obtained from the human counting in the laboratory once the process is finished). If the network is properly designed, and the range of samples is wide enough to cover all the cases, in the moment when another situation is provided (this is, a different input is supplied), the network will be capable of giving the correct value of number of pores as output.

The neural network accomplished for this application is "back propagation" type and has 2 layers and 5 neurons in its hidden layer, 5 inputs and 1 output. The output is the final number of pores per centimeter that that block of foam will have at the end of the foam manufacturing process. The training is supervised.

In a first approach, an only neural network for the whole range of foams was designed, but the obtained error in the first stage of tests was considered too high. The objective is an error rate even lower than the one obtained by the human inspection in the laboratory.

This is why it was decided to accomplish 3 neural networks, one for each of the 3 groups in which all the foam samples have been classified: 1. the foams of clear hue and small pore; 2. the dark foams with small pore, and 3. the dark foams with big pore. The structure of each of them is similar, but the supervised training is executed in every case with different samples of the related group.

The 5 chosen inputs for the network are: the number of pores per centimeter obtained after the statistical analysis; other values extracted from the stages of morphological and statistical processing of the image, such as standard deviation of the number of pores in each line, average of histogram, moda and standard deviation of the histogram. The output is the final number of pores per centimeter that that block of foam will have at the end of the foam manufacturing process. This value is known in advance (provided by the experts) for the supervised training.

The developed software module presents a user interface. It has been allowed not only to get this control parameter but also other functionalities, such as system configuration, live grabbing, grabbed image displaying and zooming and its comparison with a previously saved reference image for each model of foam. It is also possible to select each model of the range of foams, and the storage of the results in an Excel report for registering the progress of production.

3.1.3 User interface (UIR)

To guarantee the success of a system fully dedicated to production and to make it easily accepted by the users, it is essential that the system is user-friendly. Therefore, the designed UIR has been oriented to provide with the maximum useful services. It allows:

- on-line grabbing to evaluate the quality of the foam sample wanted to be inspected
- zoom to observe with high accuracy the pore quality, important for the user
- a reference image is loaded of the same model. It is stored a reference image for each model
- An Excel report is generated to store all the results of every inspected sample

This is the user interface:

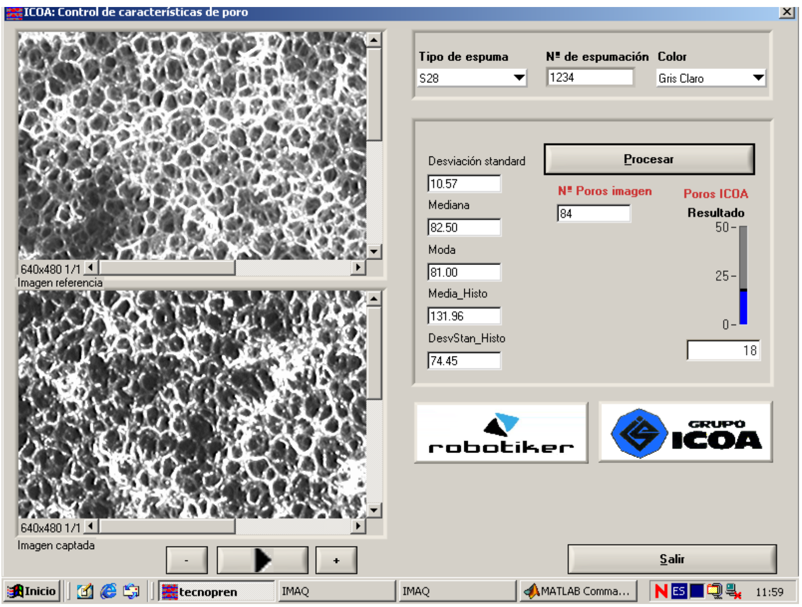


Figure 5. User interface of the application

4. TESTS AND RESULTS

The prototype is now being tested at production facilities. There are two aims for the tests:

- To verify the validity of the obtained value with regard to the real value.
- To check the reliability of these results and the robustness of the accomplished system.

At this stage, the system is just been installed in the production plant, but it is not still on-line, and the results are still preliminary. It is expected to install it on-line in the manufacturing machine and test the real robustness of the proposed methodology.

4.1. RELIABILITY OF THE SYSTEM

To check the trustworthiness of the system, several tests have been done with different models of foam. It was verified the existing error between the obtained output value and the real counted value by a foaming counter at the end of the process. These ones are some of these results, with two images of the same model in each case:

Foam model	Pores system	Real pores
Srf	20	20
	19	20
S28	19	18
	18	18
S30hfr	18	18
	18	18
S40bpd-1	31	30
	31	30
S40bpd-2	29	27
	29	27
Sh60	11	12-13
	13	12-13

The maximum error is close to 8% meanwhile the average error is of 3%. They are even smaller than the ones obtained in the laboratory in two different random samples of the same foam.

4.2. REPETITION OF RESULTS AND ROBUSTNESS OF THE SYSTEM

The initial robustness and reliability of the system was evaluated, taking into account that this is not the on-line and definitive system. For that, the average value and the standard deviation were calculated with 10 images from the same piece of foam. These images are different each other.

As example, the results obtained for a type of foam are shown next:

Model	Image-sample	Pores system	Real pores
S40bpd	1	30	30
	2	30	30
	3	31	30
	4	30	30
	5	31	30
	6	30	30
	7	31	30
	8	30	30
	9	30	30
	10	30	30

Average value: 30.3

Standard deviation: 0.42

These initial results allow stating the repetition of the values provided by the system and its reliability. They will have to be verified by all the posterior results. The use of neural networks has implied a big advance in the analysis of data and has supplied a trustworthy solution. Besides the data of number of pores per centimeter (initial requirement of the foam producer company), the added value that the functionality of the user interface provides makes the system really useful for the foam producer.

At the moment, this application is operative in the manufacturing plant ICOA and has been installed by INGENIERIA DEL POLIURETANO FLEXIBLE, S.L. Nowadays, the neural network is being improved by training it with samples of new models of foams. Once the network is trained with this bigger and bigger range, the system is expected to have an even more trustworthy response and it will be susceptible of use for all the materials of ICOA.

5. CONCLUSIONS AND FUTURE TRENDS

The application of machine vision technologies in the industrial sector of the foam is scarce; being this chemical process characterized by a manual control of the worker according to his experience and knowledge. This fact limits the efficiency of the manufacturing process and the quality of the resulting element. The developed application shows many advantageous features:

- A solution is presented adapted to the problem from the very moment of grabbing, with architecture of lighting and camera suitable for the requirements of the user and inexistent in the market.
- It is considered an "on-line" analysis of the image in the very first stage of the foaming process, but giving the similar response to the one obtained at the laboratory in the end. Having this in mind, proper information of how it is being formed makes it possible to act over it, and in this way, to improve the final quality of the foam. Before, this information was only available 2 days later in the laboratory, once the chemical foaming process was finished.

The application of methods based on neural networks in the process is absolutely novel and pioneering. The reached results validate the use of neural networks, as well as the approach of the previous morphological and statistical analysis. This makes it valid the use of Artificial Intelligent techniques for controlling manufacturing process in an intelligent, fast, reliable and accurate way. This implies a step forward in the industrial processes.

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REFERENCES

[1] *Symon Haykin.. Neural Networks. A comprehensive foundation. Prentice Hall, 1994.*

[2] *] Principe, Euliano, Lefevre*. Neural and Adaptive Systems*. John Wiley & sons, 2000.*

[3] *Gonzalo Pajares, Jesús M. De la Cruz.* Visión por computador. *Ra-Ma, 2001..*

[4] *Kachigan. Statistical analysis. An interdisciplinary Introduction to Univariate & Multivariate methods. Radius Press, 1986*

[5] *Matlab. Neural Network Toolbox. Matlab 7.0, 2004.*

[6] *Fernández Salazar, Landa Amezua. Técnicas y aplicaciones de la iluminación. MacGrawHill, 1997.*

[7] *J. J. Shah, M. Mäntylä and D. S. Nau, Advances in Feature Based Manufacturing, Elsevier, 1994.*

[8] *http://www.e-manufacturing.com/.*