DEFECTIVE METAL END DETECTION WITH A FUZZY SYSTEM

Perfecto Mariño Espiñeira, Vicente Pastoriza Santos,
Miguel Santamaría Sánchez, Emilio Martínez Expósito

Universidad de Vigo, Departamento de Tecnología Electrónica, E.T.S. Ingenieros Industriales,
Campus Lagoas-Marcosende, 36310 Vigo, ESPAÑA

Keywords: Image processing, fuzzy control, machine vision system, intelligent fault detection.

Abstract: The authors have been involved in developing an automated inspection system, based on machine vision, to improve the repair coating quality control (RCQ control) in can ends of metal containers for fish food. The RCQ of each end is assesed estimating its average repair coating quality (ARCQ). In this work we present a fuzzy model building to make the acceptance/rejection decision for each can end from the information obtained by the vision system. In addition it is interesting to note that such model could be interpreted and supplemented by process operators. In order to achieve such aims, we use a fuzzy model due to its ability to favour the interpretability for many applications. Firstly, the easy open can end manufacturing process, and the current, conventional method for quality control of easy open can end repair coating, are described. Then, we show the machine vision system operations. After that, the fuzzy modeling, results obtained and their discussion are presented. Finally, concluding remarks are stated.

1 INTRODUCTION

In the food canning sector, in the easy open can end manufacturing process, to guarantee the desired product lifespan, a manual, nondestructive testing (NDT) procedure is carried out. Due to the high processing rate, only an small part of each lot is verified. Therefore, it is important to develop an automated inspection system to improve the easy open can end repair coating quality control process (all can ends are checked, and inline). It is for this reason that we had been involved in the design and implementation of an inline, automated machine vision system to evaluate the repair coating of the can ends, that we have named end repair coating inspection system (ERCIS). In this work we explore the use of fuzzy models to make the acceptance/rejection (A/R) decision for each can end. A Takagi-Sugeno-Kang fuzzy model is developed using a neuro-fuzzy modeling. The remainder of this paper is organized as follows: in the next section we provide an overview of the easy open can end manufacturing process and its repair coating quality control process. Section 3 shows the machine vision system operations. Then, Section 4 describes the fuzzy modeling. The results obtained and their discussion are presented in Section 5. Finally, we state concluding remarks in Section 6.

2 BACKGROUND

A can consists of can body and can end, which are made from aluminum or steel. Can ends, from henceforth ends, are used for all type of cans and can be standard or easy open. In this paper, we study a specific end format named 1/4 Club, with an easy-open tab in one of its corners.

2.1 Easy open end manufacturing process

Easy open ends are made from pre-coated metal coils or sheets. Ends are stamped from coil or sheets in a press. After stamping, the ends are scored in a predefined geometric shape (scoreline) intended to ease the end opening. Finally, a tab is attached to form an easy open end. These steps are performed after the end piece has been coated and therefore damage the coating, especially on the scoreline. Repair coating, which has a fluorescent pigment, is applied after these steps on the required area to restore the integrity of the coating.

Mariño Espiñeira P., Pastoriza Santos V., Santamaría Sánchez M. and Martínez Expósito E. (2005).
DEFECTIVE METAL END DETECTION WITH A FUZZY SYSTEM.
In *Proceedings of the Second International Conference on Informatics in Control, Automation and Robotics*, pages 270-274

2.2 Easy open end repair coating quality control

Presently a visual inspection of the easy open ends is carried out (Lin et al., 1998; CFIA, 1998), where the inspectors assess the repair coating on the scoreline. This visual inspection is a manual and NDT procedure. To assist in this end inspection the repair coating has a fluorescent pigment that stands out as a bright light blue when excited by an ultraviolet black light, while the background color remains unchanged. This inspection is based on a statistical sampling. It is because of this and the high rate of the repair coating process (100 to 500 ends per minute, depending on the end format) that only a small part of each lot is verified. Therefore, defective can ends can be sent to the canneries.

3 MACHINE VISION SYSTEM OPERATIONS

The vision algorithm running on ERCIS take care of inspects the repair coating quality (RCQ) on each end. The vision algorithm has two parts: one offline and other inline. The flowchart of ERCIS is shown in Fig. 1.

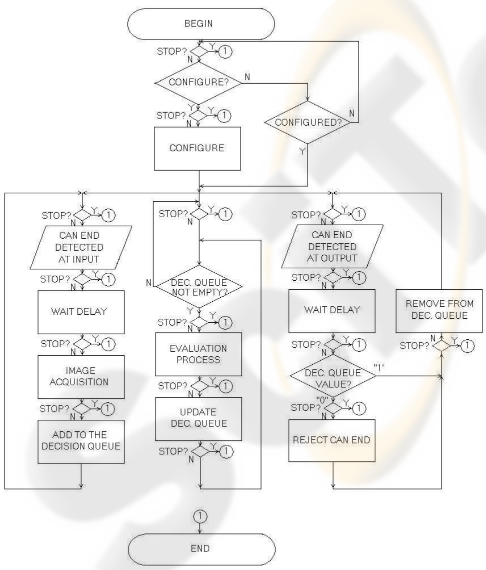

Figure 1: Flowchart of ERCIS

3.1 Offline

Before the ERCIS begins the continuous or online inspection of ends is necessary to configure or reconfigure a series of parameters that will be used later in the inline processing.

3.1.1 Time delay configuration

An offline adjustment can be necessary to set the delay, input delay time (IDT), between the sensor at the ERCIS input detecting the end and the end reaching the camera, and the delay, output delay time (ODT), between the ERCIS output sensor detecting the end and the end arriving next to the rejection system.

3.1.2 Region of interest definition

The scoreline is enclosed in the region of interest (ROI). Each quadrant of this ROI, and by simmetry, the whole ROI is geometrically modeled by the parameters b and r (Fig. 2). Besides these parameters it is necessary to add an e width to the ROI (Fig. 2).

$$ROI_{\text{HOR}} = f\,(b, r, e) \tag{1}$$

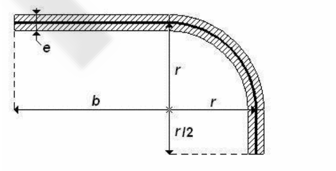

Figure 2: End ROI quadrant geometrical model

Parameters will be adjusted before the line continuous working, and they depend directly on the distance between and and camera (working distance).

3.1.3 Parameter configuration to decide the end rejection

In order to take the A/R decision for each end during the inline processing is necessary to offline configure the Minimum Average Repair Coating Quality (MARCQ) of the end to not reject it. The object of this parameter can be seen on Subsection 3.2.2.

3.2 Inline

The end continuous inspection can only start after the offline parameter configuration. This inline process has for each end the following sequence of steps:

3.2.1 Acquisition

This process undertakes the detection of the ends and acquisition of images of them. It is divided into the subprocess: end detection before the ERCIS, and end acquisition.

3.2.2 Evaluation

If the decision queue is not empty then an image has already been acquired and can be processed. This process has the following steps:

- End center location and end orientation.
- ROI rectification. The ROI is converted into a straight line strip to ease its analysis. This strip is a Look-up-Table (LUT) whose size is $n \times e$ pixels. The length n, in which is divided the ROI perimeter, depends on the selected resolution. The rectification method employed selects for each one of $n \times e$ pixels the nearest 4-neighbour (González and Woods, 2002).
- Repair coating quality: The RCQ is assessed analyzing one-by-one all the n positions of the LUT by means of the model obtained in Section 4.
- End A/R decision: The average repair coating quality (ARCQ) is computed from the RCQ values at the n positions in which have been divided the ROI. Then, an end have to be rejected when the condition ARCQ<MARCQ is given (see the meaning of MARCQ in Subsection 3.1.3).
- Update the decision queue: The decision queue must be updated after making the A/R decision of each end.

3.2.3 Expulsion

This process is subdivided in: end detection after the ERCIS, and end expulsion.

3.2.4 Stop

If stop signal is activated then the process goes to the flowchart end with independence of the current state of the process.

4 MODELING

In order to evaluate the RCQ on each one of n positions of the LUT, a set of a few attributes that contain most of the relevant information on each one of the n positions is studied. The 9 attributes computed from each e-pixel group of n^{th} LUT position are: Maximum pixel intensity (Max), Minimum pixel intensity, Mean pixel intensity is a measure of central tendency (location), Median pixel intensity is a measure of central tendency (location), Pixel intensity standard deviation (Std) is a measure of dispersion, Pixel intensity skewness is a measure of the asymmetry, Pixel intensity center of mass (CoM), Pixel intensity moment of inertia about an axis passing through the CoM, and Pixel intensity bisector.

A fuzzy inference system (FIS) (Kosko, 1992; Yager and Zadeh, 1994; Klir and Yuan, 1995), whose inputs are the selected attributes, will be used to evaluate the RCQ on each of the n positions. As an excessive number of inputs prevents the interpretability of the underlying model and increases the computational burden, we look for a model with a trade off between high accuracy and reduced number of inputs. We got a modeling problem with 9 candidate inputs and we want to find the 3 most influential inputs as the inputs of the model. We so can build 84 fuzzy models, each one with a different combination of 3 inputs. The proposed FIS model is a Takagi-Sugeno-Kang (TSK) inference system (Takagi and Sugeno, 1985; Sugeno and Kang, 1988). These models are suited for modeling non-linear systems by interpolating multiple linear models. The TSK model is designed with zero order (singleton values for each consequent), 3 of 9 attributes as inputs and RCQ as output. The TSK model is developed using the adaptive neuro-fuzzy inference system (ANFIS) algorithm (Jang, 1993; Jang and Sun, 1995).

We use a quick and straightforward way of neuro-fuzzy modeling input selection using ANFIS to improve the interpretability (Jang, 1996). This input selection method is based on the hypothesis that the ANFIS model with smallest RMSE (root mean squared error) after one epoch of training has a greater potential of achieving a lower RMSE when given more epochs of training.

Representative input-output data set of the system should be selected to tune a model. We have only worked with a specific end format named 1/4 Club, with an easy-open tab in one of its corners. We have selected a collection of 11 ends that agglutinate all possible end repair coating defects. The obtained LUT for each end has a length n of 702 positions, with a width e of 19 pixels. After removing instances with outlier values, the data set was reduced to 6669 entries. This data set is divided into training and testing sets of size 3335×19 and 3334×19 respectively. The testing set is used to determine when training should be terminated to prevent overfitting.

It has been selected grid partitioning as the ANFIS partition method. The best model after one epoch of training selects as input attributes the maximum (Max), the standard deviation (Std), and the center of mass (CoM). The problem is that this partitioning leads to a high number of rules, $2^3 = 8$ rules for each model.

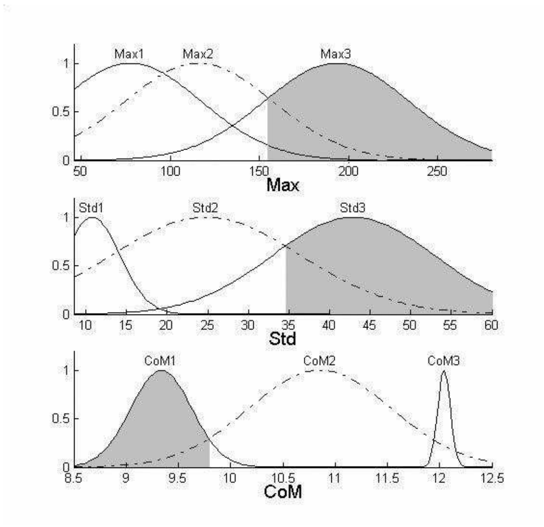

Figure 3: Fuzzy model membership functions

In order to reduce the model complexity we use subtractive clustering (Chiu, 1994) for the 3 inputs previously selected. We have selected the model with range of influence 0.5 that has 3 rules that gives a RMSE of 0.3106 for training and 0.3091 for testing.

Table 1: Fuzzy Models Rules

Rules	*Repair Coating Quality*
If Max is Max1 & Std is Std1 & CoM is CoM2	S1[5]* Defective
If Max is Max2 & Std is Std2 & CoM is CoM3	S1[5] Defective
If Max is Max3 & Std is Std3 & CoM is CoM1	S2[10] Acceptable

*S[m] = singleton (m=mean)

We can further refine said model performance applying extended ANFIS training. The final model obtained use Max, Std, and CoM as model inputs, RCQ as output, and 3 rules (Table 1) to define relationships among inputs and output. The membership functions for each input feature are shown in Fig. 3 and singleton values for each consequent in Table 1.

This model gives a RMSE of 0.0102 for training and 0.0101 for testing, more similar values which indicate that there is no overfitting. Regarding the interpretability of the model and from its rules, is deduced that the RCQ at n^{th} LUT position is acceptable if and only if at said position, see Fig. 3 and Table 1, the maximum pixel intensity is higher than 150 and the standard deviation is higher than 35 and the center of mass is close to 9.5, which is the e-pixel group center. The interpretation of this is the following:

- The higher the maximum pixel intensity, the higher the lacquer quantity.
- As a defect region has little or no lacquer and is more uniformly distributed than an acceptable region, then the pixel intensity is less scattered (less Std) in defect regions.
- As the ROI is positioned in the way that the scoreline is at its center zone, and as an acceptable end has the highest lacquer level at scoreline, then at each one of n LUT positions the nearer of the e-pixel group center is the CoM, the better the RCQ.

5 RESULTS

The RCQ of each end is assessed estimating its ARCQ. This average quality is computed from the RQ of the n positions in which has been divided the ROI, and where the RCQ at each n position is analyzed by means of the FIS obtained.

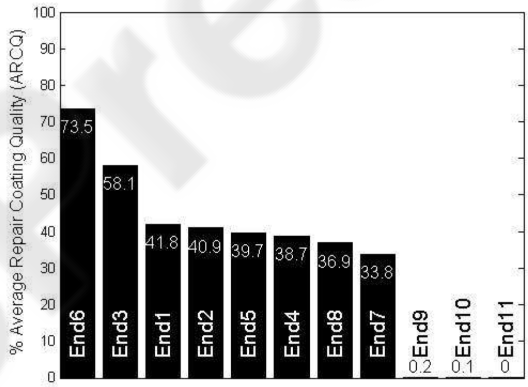

Figure 4: ARCQ classification of the ends

Fig. 4 shows the ARCQ classification of the 11 ends previously used to tune the fuzzy model. The ends were sorted in descending order of ARCQ.

As each end have to be rejected when ARCQ<MARCQ is given (see the meaning of MARCQ in Subsection 3.1.3) then what ends are rejected will depend on the MARCQ value selected. For example, if MARCQ is 80 then all 11 ends are rejected. This flexibility to be able to modify the rejection threshold is an important property of the ERCIS.

But the most important result is that, with independence of the MARCQ selected, the ARCQ classification agrees with the one made by an expert human inspector.

6 CONCLUDING REMARKS

We have been involved in the implementation of a machine vision system to improve the repair coating quality control of the easy open can end manufacturing process. The system has the following properties:

- End classification in agreement with the one made by an expert human inspector.
- Flexibility to be able to modify the rejection threshold.
- Interpretability supplied to the operators in order to find out the failure causes and reduce mean time to repair (MTTR) during failures.
- Total inspection of 100% end production.

In spite of the fact that the end repair coating process of only one end format (1/4 Club) has been studied, as this process is common to all formats, it is reasonable to think that fuzzy models like the found model can be obtained to make the A/R decision for another end format.

All this leads to the conclusion that is possible to design an inline, automated machine vision system, which only extracting the ARCQ from each end, makes a right A/R decision. ANFIS, the neuro-fuzzy modeling technique used to optimize the fuzzy model, provided excellent prediction accuracy.

In the future we will study the existence of models that estimate the easy open can end repair coating process failure causes. Furthermore, we will research the application of coevolutionary genetic fuzzy modeling techniques that improve the interpretability without a significant loss of accuracy.

REFERENCES

CFIA (1998). Metal can defects; identification and classification manual. Technical report, Canadian Food Inspection Agency (CFIA).

Chiu, S. (1994). Fuzzy model identification based on cluster estimation. *J. of Intelligent & Fuzzy Systems*, 2(3):267–278.

González, R. and Woods, R. (2002). *Digital Image Processing*. Prentice Hall, Upper Saddle River, NJ, 2nd edition.

Jang, J. (1993). Anfis: Adaptive network based fuzzy inference system. *IEEE, Transactions on Systems, Man, and Cybernetics*, 23(3):665–685.

Jang, J. (1996). Input selection for anfis learning. pages 1493–1499. Proceedings of the IEEE International Conference on Fuzzy Systems.

Jang, J. and Sun, C. (1995). Neuro-fuzzy modeling and control. volume 83(3), pages 378–406. The Proceedings of the IEEE.

Klir, G. and Yuan, B. (1995). *Fuzzy Sets and Fuzzy Logic: Theory and Applications*. Prentice Hall, Upper Saddle River, NJ.

Kosko, B. (1992). *Neural Networks and Fuzzy Systems: A Dynamical Systems Approach to Machine Intelligence*. Prentice Hall, Englewood Cliffs, NJ.

Lin, R., King, P., and Johnston, M. (1998). Examination of metal containers for integrity. In Merker, R., editor, *FDAs Bacteriological Analytical Manual Online*. Center for Food Safety and Applied Nutrition (CFSAN), U.S. Food & Drug Administration (FDA).

Sugeno, M. and Kang, G. (1988). Structure identification of fuzzy model. *Fuzzy Sets and Systems*, 28(1):15–33.

Takagi, T. and Sugeno, M. (1985). Fuzzy identification of systems and its applications to modeling and control. *Transactions on Systems, Man, and Cybernetics*, 15(1):116–132.

Yager, R. and Zadeh, L., editors (1994). *Fuzzy Sets, Neural Networks, and Soft Computing*. Van Nostrand Reinhold, New York.