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AUTOMATIC CHARACTER RECOGNITION IN PORCELAIN WARE

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Abstract: This paper presents an automatic serial number recognition system based on computed vision techniques and machine learning. The serial number is engraved on the backside of porcelain ware. The approach uses standard algorithms for digit segmentation and a deep learning approach for the recognition. The system is developed within a project in collaboration with one of the biggest porcelain ware producer in Europe.

Keywords: *Deep Learning, Computer Vision, Digit Recognition, Porcelain.*

I. INTRODUCTION

With the new advances in robotics, the porcelain manufacturing industry is taking full advantage of the power of automatization. Porcelain manufacturers are well robotized, with hundreds of robots connected to machine vision systems.

The porcelain manufacturing process has several phases: the mass preparation, powder atomization, object shaping, burning I, glazing, burning II, quality control, sorting. Defect detection is an important problem in the porcelain industry which is currently performed by employees. Defects may appear at different stages of the manufacturing process. While manufacturing any type of porcelain ware, in the case of a defect, the error is usually propagated to all the series in the production. The root of the problem can be found in many different parts of the process: the raw materials [1] (clay, feldspar, or silica) might be contaminated or any of the processing steps [2] (crushing, mixing, forming the shape, glazing, firing, painting) might contain a malfunctioning machine which provokes the defect.

The quality control is performed at the end of the manufacturing process after the sorting phase, but also at two intermediate steps after burning I and glazing phases. However, at the time being, the quality control does not take, the advantage of the power of automatization like all other phases of the manufacturing process, and it is currently performed by human employees.

This paper presents a research task performed within a bigger research project in which we have investigated the automatization of the quality control at one of the largest porcelain manufacturers from Romania, IPEC S.A. The research project is focused on optimizing the quality control at IPEC by automatic defect detection and removing the defective items in the early stages of the production [7], [8]. By improving the quality control process, we have estimated that the porcelain manufacturer could save up to 60% of the cost of the human resources and up to 20% of the production costs.

This paper discusses only the automated identification of the figures embossed on the back of the porcelain ware. In order to identify the parts of the process, characters (numbers and letters) are engraved in the porcelain ware. Such marks must be covered and disappear after the glazing phase. However, for quality control it is extremely important to identify such marks that may offer important information in case of defective products. The symbols engraved are representing the type of product, identification of the lump of raw material used, and the shift within the porcelain ware was produced. Our approach seeks to detect and recognize these symbols in order to help in the quality control process, aiming to facilitate defect measurements and rectifications in the porcelain ware manufacturing..

As far as the authors know, there is no bibliographic research literature available on computer vision solutions for plate inspection, other than extracting texture features for detecting defects on ceramics and tiles [3], [4], [9]. However, it is an emerging technology in the global ceramic industry [6], and a standardization on the determination of ceramics quality has been established by the International Standard Organization (ISO) in the SNI ISO 10545-2:2010 document [7].

The approach presented hereby has been experimentally tested by using round plates on which the symbols are embossed on the backside of the plate. The images of the plates are taken in a real manufacturing workflow

The paper is organized as follows: Section II describes in more detail the addressed problem, Section III and IV describe our approach and problem solution, Section V presents the experimental results and Section VI discloses conclusions and directions for future research.

II. PROBLEM DESCPRIPTION

The problem is to correctly identify the figures embossed on the backside of a plate. The image of the plate is taken while the plate is passing on a conveyor belt. An example of such an image is presented in Figure 1.

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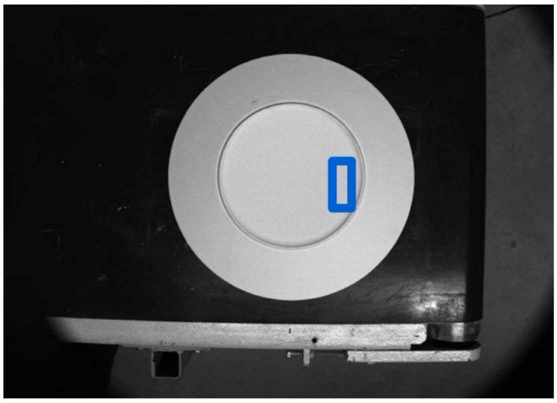

Figure 1. The original image with the engraved characters highlighted in the blue box.

On the backside of the plate there are engraved some characters which identify the plate. The engraved symbols are organized into three groups which represent: 1) the sack of material (4 symbols); 2) the work shift (1 symbol: I, P, E or C); and 3) the product type (3 symbols). A magnified image of the three groups of symbols engraved on the backside of each plate are shown in Figure 2.

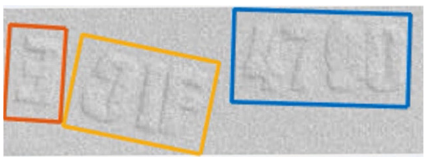

Figure 2. The three set of characters engraved on the backside of the plate.

In order to detect and recognize these symbols, we had to segment the image, which means to detect each of these three groups of characters in the image and after that to detect each individual character from the group and to identify it. As one may notice in Figure 2, some characters might be reversed, the left and middle group of characters from Figure 2, and this aspect has also to be considered.
We will describe our solution to this problem in the following two sections. Our solution is composed by two parts: segmentation (Section III) and identification based on classification using deep learning techniques (Section IV), schematically shown in Figure 3.

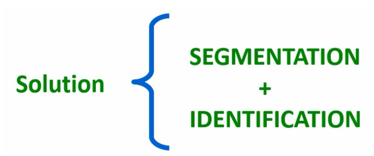

Figure 3. Solution based on segmentation and identification.

III. SEGMENTATION PROCESS

The final goal of the segmentation process is to be able to get individual characters from the original image. The segmentation process is illustrated in Figures 4 to 9. It starts from an original image of the plate as it is shown in the top image in Figure 4 and it proceeds with several intermediate steps to finally end in individual characters as it is shown in the bottom of Figure 4.

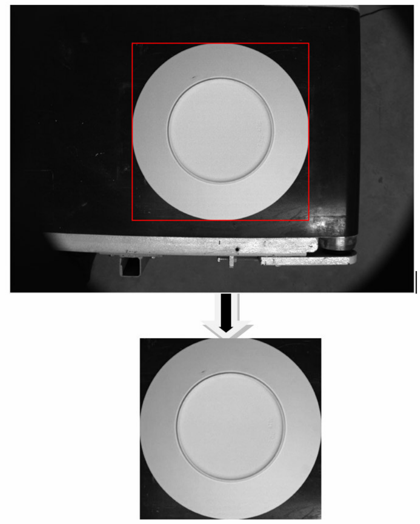

Figure 4. The first step of the segmentation process.

In order to segment the individual symbols, the geometrical properties of the plates are searched in the image in a sequential manner. The segmentation process consists of four steps: 1) Outer bounding box of largest object; 2) Segmenting the inner circle; 3) Performing of several binarizations until the 3 boxes of the expected area are found; 4) Studying the 3 groups of characters one by one and identifying individual characters. These steps of the segmentation process are detailed below:
1. *Outer bounding box of largest object.* We segment the image using the outer bounding box of the largest object, and we obtain the image containing only the image of the plate. 8-connected components of contiguous regions of a binarized version of the image have been studied, measuring their area and perimeter. This allowed us to select the largest area (corresponding to the plate) and finding the inner circle using Equation 1.

$$circularity = perimeter / 4 * \pi * area \quad (1)$$

In the lower image of Figure 5, the inner circle is drawn in red.

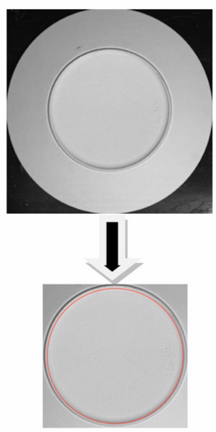

Figure 5. The second step of the segmentation process.

2. *Segmenting the inner circle*. We continued with the image obtained at the previous step. The geometric properties of the components have been studied. Two circles were obtained namely: the outer and the inner circles of the plate. By computing the diameter, we could detect the outer and inner circles. We have segmented only the inner circle.

3. The inner circle area was again binarized, the resulting edges were enlarged and, again, 8-connected components of contiguous regions have been studied to detect the 3 groups of letters. Several binarizations have been applied until the 3 boxes of the expected area were found. Only 2 binarization were enough to find the 3 groups. We moved the threshold incrementally until we find the 3 groups.

4. We have studied the 3 groups of characters one by one. In each group, the projection of the characters into the X-axis was studied to separate the individual letters. We segmented each group of letters with a fixed size, which was of 59x26 pixels.
The segmentation of each letter was performed as follows: we considered the letters from each group in Figure 6, separately.

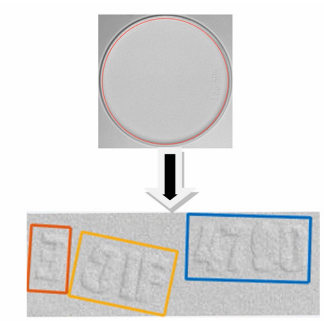

Figure 6. The third step of the segmentation process.

After binarizing a group of letters, the pixels were projected into the X-axis, as shown in Figure 8. Each "*valley*" in Figure 8 identifies the pixels where we cut the image from Figure 7, to get individual letters. In this case: pixels 20-30 identify the separation between the first two characters from Figure 7, pixels 40-50 identify the separation between the second and the third character, and the third valley, pixels 65-75 identify the separation region between the third and the fourth character in Figure 7.

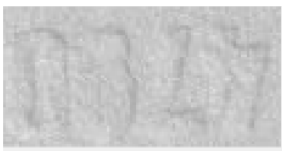

Figure 7. Image to be segmented.

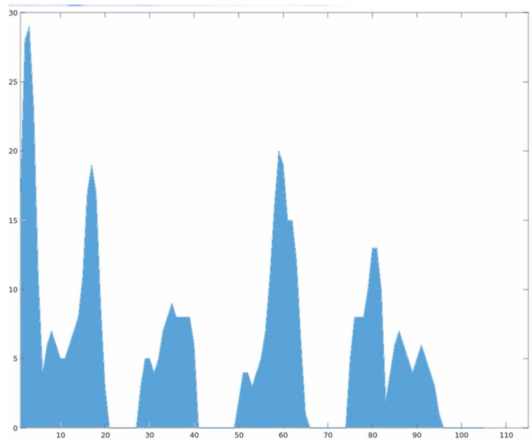

Figure 8. Projections on X-axis.

Having done these, we could finally find the individual characters as it is illustrated in Figure 9. Note that this character might not appear in a straight position, can be found upside down and might not be complete after the last segmentation.

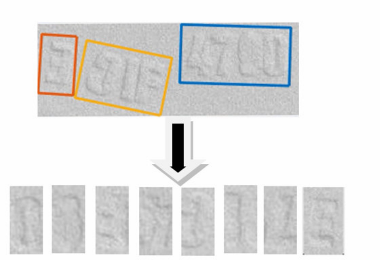

Figure 9. The fourth step of the segmentation process.

IV. CONVOLUTIONAL NEURAL NETWORKS

Convolutional neural networks (CNNs) are deep, feed-forward artificial neural networks, which are most commonly applied for image analysis tasks.
Convolutional neural networks have several convolution layers defining the network, and these layers are applied over the input layer. Each layer applies different filters to the data that can either determine pixel boundaries or detect simple shapes or high-level features such that the last layer can ultimately perform the classification using the high-level features.
We trained a CNN on the set of characters images. It is a supervised classification task, each image being associated with the symbol that appears in the image.

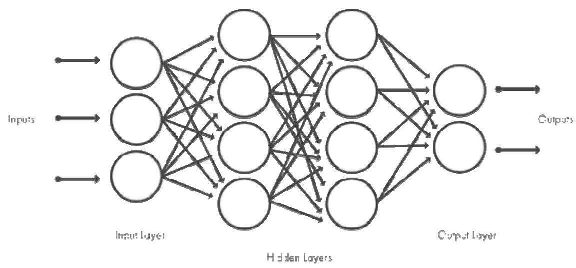

Figure 10. General aspect of a Neural Network.

To recognize the signs (numbers, letters and symbols) a Deep Learning type network has been used for classification of type convolutional neural network (CNN). This network is composed of the following layers:

- **Image Input Layer:** this layer has as input the images of size 53x26 in gray scale. During the training they are reordered randomly at the beginning of each period and therefore it is not necessary for the images to be ordered. Although the images are in subdirectories with the names of the desired classification.
- **Convolutional Layer:** this layer performs a series of convolutions with 7x5 size filters to extract the characteristics. The number of filters, that is, the number of neurons that connect to the same region of the input is 26.
- **Batch Normalization Layer:** this layer normalizes the activations and gradients so that the values are comparable and network training is easier.
- **ReLU Layer:** this layer uses a non-linear activation function of rectified linear unit (ReLU) type, to make all values non-negative.
- **Max Pooling Layer:** this layer reduces the special size by removing the redundant information.
- **Fully Connected Layer:** the neurons of this layer connect with all the neurons of the previous layer to combine the characteristics learned in the previous layers.
- **Softmax Layer:** this layer normalizes the outputs of the previous layer so that the outputs of this layer are positive values that add up to one. This means that they can be used as classification probabilities by the next layer.
- **Classification Layer:** this layer classifies the image into one of the (mutually exclusive) classes and calculates the loss function.

Next, the characteristics of some of the used layers are shown. Note that the input layer size corresponds to the size of the segmented individual letters. The convolutional layer is quite small, which means a time-consuming process, but it is necessary to obtain the main characteristics of the noisy images we have. The same happens in the polling layer, in which the rectangular regions in which the pooling is performed are small to concentrate in small characteristics.

ImageInputLayer = [53 26 1]
convolution2dLayer = ([7,5], 26)
reluLayer
maxPooling2dLayer(2, ‘Stride’,2)
fullyConnectedLayer(18)
softmaxLayer

V. RESULTS

We used a date set containing 17 images of plates. The images were acquired with a Basler acA1300-30gm GigE camera [10] and the VBAI (Vision Builder for Automated Inspection) module from National instruments [10]. All the individual collected characters have been manually sorted and labeled into their respective category, resulting in 18 different characters. With the resulting database, a Convolutional Neural Network was trained using the 75% of the examples, while the rest was used for testing. This way, we were able to correctly classify 99% of the database.

Figure 11 shows the output of the convolutional layer which has a greater value of activation when performing the identification of a number ‘7’, a letter ‘F’ and a letter ‘I’, respectively. In the first case, the maximum activation is located along the left edge of the number. In the second one, the activations mainly concentrate around the horizontal edges of the letter ‘F’. Finally, in the last case the activations appear along the right vertical and the upper horizontal edges. We could therefore conclude that the Neural Network was mainly using the edges of the characters to perform the identification.

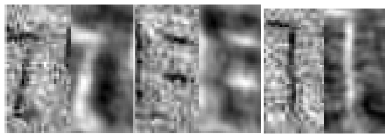

Figure 11. Maximum activation of a convolutional layer when identifying a number ‘7’, a letter ‘F’, and a letter ‘I’, respectively.

Figure 12 shows a summary of the results of the identification process. Note that to avoid confusions due to letters found upside-down, they were identified as if they were different letters, and were assigned a letter ‘r’ after the value of the character. The confusion matrix shows that, in general, the identification process was very satisfactory, showing that the only mistake was made between a number 3 which is upside-down and a letter E.

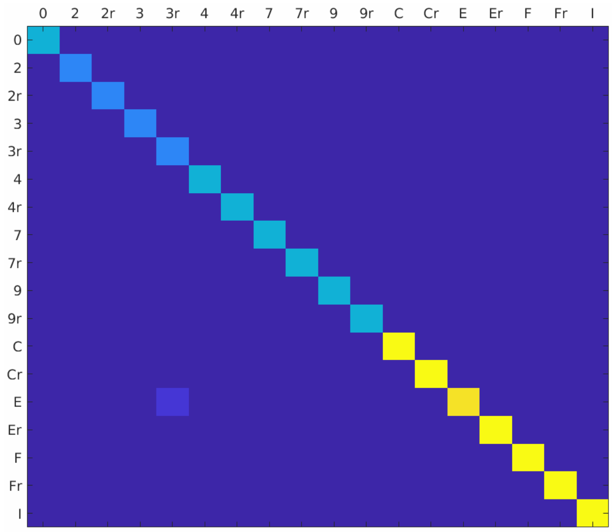

Figure 12. Correlation matrix of the identification.

The results prove that the chosen technique is appropriate for achieving good recognition results and, therefore, we plan to extend the work to more types of porcelain ware and more symbols to be distinguish.

VI. SUMMARY AND FUTURE WORKS

The presented work shows how to perform character identification during the manufacture of porcelain ware. We can conclude that the presented segmentation process performs well in round flat plates and, also, the classification of the characters based in CNNs shows a promising result.

However, we are aware that the results are concentrated in only one type of plate and a small number of possible characters. Future work will concentrate in two areas. On one hand, it will focus on parameterization of the segmentation for other type of ware and apply more general rules to avoid the need of different rules for each type of ware. On the other hand, it is necessary to enlarge the database of characters to increase the number of characters recognized and to study possible actions to detect false-positive recognitions.

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