AVI of Surface Flaws on Manufactures II

Girolamo Fornarelli
Politecnico di Bari, Italy

Antonio Giaquinto
Politecnico di Bari, Italy

INTRODUCTION

Automatic visual inspection takes a relevant place in *defect detection* of industrial *production*. In this field a fundamental role is played by methods for the detection of superficial anomalies on manufactures.

In particular, several systems have been proposed in order to reduce the burden of human operators, avoiding the drawbacks due to the subjectivity of judgement criteria (Kwak, Ventura & Tofang-Sazi 2000, Patil, Biradar & Jadhav 2005).

Proposed solutions are required to be able to handle and process a large amount of data. For this reason, neural networks-based methods have been suggested for their ability to deal with a wide spread of data (Kumar 2003, Chang, Lin & Jeng 2005, Garcia 2005, Graham, Maas, Donaldson & Carr 2004, Acciani, Brunetti & Fornarelli 2006). Moreover, in many cases these methods must satisfy time constrains of industrial processes, because the inclusion of the diagnosis inside the *production* process is needed.

To this purpose, architectures, based on Cellular Neural Networks (CNNs), revealed successful in the field of *real time* *defect detection*, due to the fact that these networks guarantee a hardware *implementation* and massive parallelism (Bertucco, Fargione, Nunnari & Risitano 2000), (Occhipinti, Spoto, Branciforte & Doddo 2001), (Perfetti & Terzoli 2000). On the basis of these considerations, a method to identify superficial damages and anomalies in manufactures has been given in (Fornarelli & Giaquinto 2007). This method is aimed at the *implementation* by means of an architecture entirely formed by Cellular Neural Networks, whose synthesis is illustrated in the present work. The suggested solution reveals effective for the detection of defects, as shown by two test cases carried out on an injection pump and a sample textile.

BACKGROUND

In the companion paper an approach for *defect detection* of surface flaws on manufactures is proposed: this approach can be divided into three modules, named Preprocessing module, Image Matching module and *Defect Detection* module, respectively. The first one realizes a pre-processing stage which enables to identify eventual defected areas; in the second stage the *matching* between such pre-processed image and a reference one is performed; finally, in the third step an output binary image, in which only defects are represented, is yielded.

The proposed solution needs nor complex acquisition system neither feature extraction, in fact the image is directly processed and the synthesis parameters of the networks are evaluated from the statistical image properties automatically. Furthermore, the proposed system is well suited for a single board *implementation*.

CNN-BASED DIAGNOSIS ARCHITECTURE

The detailed *implementation* of each module will be illustrated in the following. Successively the results obtained by testing the suggested architecture on two real cases are shown and a discussion of numerical outcomes is reported.

Preprocessing Module

The Preprocessing is realized by a *Fuzzy* *Contrast Enhancement* block. This block consists of a *Fuzzy* Associative Memory (FAM), developed as the preprocessing stage of the CNN-based system considered in (Carnimeo & Giaquinto 2002). The proposed circuit enables to transform 256-gray levels images into fuzzified ones, whose contrast is enhanced, due to the fact that their *histogram*s are stretched. To this purpose a proper fuzzification procedure is developed to define two *fuzzy* subsets adequate to describe the semantic content of patterns such as images of industrial objects, which can be classified as belonging to the **Object/ Background** class.

In an analogous way, the domain of output values has been characterized by means of two output *fuzzy* subsets defined as **Dark** and **Light**. In particular, the *fuzzy* rules which provide the mapping from original images (**O/R**) into fuzzified ones ($\mathbf{O_F}/\mathbf{R_F}$) can be expressed as:

IF $O(i, j) \in$ **Object** THEN $O_F(i, j) \in$ **Dark**
IF $O(i, j) \in$ **Background** THEN $O_F(i, j) \in$ **Light**

where $O(i, j)$ and $O_F(i, j)$ denote the gray level value of the (i, j)-th pixel in the original image and in the fuzzified one, respectively. As showed in (Carnimeo & Giaquinto 2002), the reported *fuzzy* rules can be encoded into a single FAM.

Then, a Cellular Neural Network is synthesized to behave as the codified FAM by adopting the synthesis procedure developed in (Carnimeo & Giaquinto 2002), where the synthesis of a CNN-based memory, which contains the abovementioned fuzzification rules is accurately formulated.

Contrasted images present a stretched *histogram*. This implies that such operation minimizes the effects of image noise, caused by environmental problems like dust or dirtiness of camera lenses. Moreover, it reduces the undesired information due to the combination between the non uniformity of the illumination in the image and the texture of the manufacture (Jamil, Bakar, Mohd, & Sembok 2004).

Image Matching Module

In Figure 1 the block diagram corresponding to the Image Matching module is reported. The target of this module consists of finding the best *matching* between the images yielded by processing the acquired image and the reference one. To this purpose the image $\mathbf{O_F}$ is shifted by one pixel into the four cardinal directions (NORTH; SOUTH, EAST and WEST), using four space-invariant CNNs (T. Roska, L. Kek, L. Nemes, A. Zarandy & P. Szolgay 1999) and obtaining the images $\mathbf{O_{FN}}$, $\mathbf{O_{FS}}$, $\mathbf{O_{FE}}$ and $\mathbf{O_{FW}}$. Successively the switch S_1 changes its position, excluding the image $\mathbf{O_F}$. The reference image $\mathbf{R_F}$ is subtracted by the images $\mathbf{O_{FN}}$, $\mathbf{O_{FS}}$, $\mathbf{O_{FE}}$ $\mathbf{O_{FW}}$ and $\mathbf{O_F}$, then the number b_N, b_S, b_E, b_W and b_0 of black pixels in the resulting images $\mathbf{D_N}$, $\mathbf{D_S}$, $\mathbf{D_E}$, $\mathbf{D_W}$ and $\mathbf{D_0}$ are computed. The image, which best matches with the reference one, presents the maximum numbers of black pixels. Therefore, such value drives the switch S_2, which allows to feedback the image that best matches with the reference one. In this way the image which presents the minimum difference becomes the input for a successive computational step. The processing is repeated until $\mathbf{D_0}$ presents the best *matching*. When this condition is satisfied, the difference image **D** between $\mathbf{D_0}$ and $\mathbf{R_F}$ is computed. As it can be noticed the operations needed for each directional shift can be carried on simultaneously, reducing the computational time at each step.

Defect Detection Module

The third part of the suggested architecture is a *Defect Detection* module. The subsystem is synthesized with the aim of computing the output binary image **F**, in which only the defects are present. Such module is composed by the sequence of a Major Voting circuit, a CNN associative memory for *contrast enhancement* and a Threshold circuit. The corresponding CNN-based *implementation* is obtained by considering space invariant networks.

In detail the Major Voting circuit minimizes the number of false detections caused by the presence of noise, highlighting the dents or those flaws which lead to a changing in the reflectance of light in the original image. The output of the Major Voting block $\mathbf{D_M}$ feeds a CNN working as the associative memory described in the previous Preprocessing module subsection. This operation provides an output image $\mathbf{D_{MF}}$ whose *histogram* is bimodal. In this kind of image the selection of a threshold, which highlights the defects, results feasible. In fact, a proper value is given by the mean of the modes of the *histogram*. Then, this image is segmented by means of the corresponding space-invariant CNN (T. Roska, L. Kek, L. Nemes, A. Zarandy & P. Szolgay 1999), obtaining the corresponding binary image **F**. In this way errors corresponding to incorrect identification of defects are minimized because only flaws are visible after the *segmentation*.

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