AVI of Surface Flaws on Manufactures I

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INTRODUCTION

The defect detection on *manufactures* is of utmost importance in the optimization of industrial processes (Garcia 2005). In fact, the industrial *inspection* of engineering materials and products tends to the detection, localization and classification of *flaws* as quickly and as accurately as possible in order to improve the production quality. In this field a relevant area is constituted by visual *inspection*. Nowadays, this task is often carried out by a human expert. Nevertheless, such kind of *inspection* could reveal time-consuming and suffer of low repeatability because the judgment criteria can differ from operator to operator. Furthermore, visual fatigue or loss of concentration inevitably lead to missed defects (Han, Yue & Yu 1999, Kwak, Ventura & Tofang-Sazi 2000, Y.A. Karayiannis, R. Stojanovic, P. Mitropoulos, C.Koulamas, T. Stouraitis, S. Koubias & G. Papadopoulos 1999, Patil, Biradar & Jadhav 2005).

In order to reduce the burden of human testers and improve the detection of faulty products, recently many researchers have been engaged in developing systems in Automated Visual *Inspection* (AVI) of *manufactures* (Chang, Lin & Jeng 2005, Lei 2004, Yang, Pang & Yung 2004). These systems reveal easily reliable from technical point of view and mimic the experts in the evaluation process of defects appropriately (Bahlmann, Heidemann & Ritter 1999), even if defect detection in visual *inspection* can become a hard task. In fact, in industrial processes a large amount of data has to be handled and *flaws* belong to a great number of classes with dynamic defect populations, because defects could present similar characteristics among different classes and different interclass features (R. Stojanovic, P. Mitropulos, C.Koullamas, Y. Karayiannis, S. Koubias & G. Papadopoulos 2001). Therefore, it is needed that visual *inspection* systems are able to adapt to dynamic operating conditions. To this purpose *soft computing techniques* based on the use of Artificial Neural Networks (ANNs) have already been proposed in several different areas of industrial production. In fact, neural networks are often exploited for their ability to recognize a wide spread of different defects (Kumar 2003, Chang, Lin & Jeng 2005, Garcia 2005, Graham, Maas, Donaldson & Carr 2004, Acciani, Brunetti & Fornarelli 2006). Although adequate in many instances, in other cases Neural Networks cannot represent the most suitable solution. In fact, the design of ANNs often requires the extraction of parameters and features, during a *preprocessing* stage, from a suitable data set, in which the most possible defects are recognized (Bahlmann, Heidemann & Ritter 1999, Karras 2003, Rimac-Drlje, Keller & Hocenski 2005). Therefore, methods based on neural networks could be time expensive for in-line applications because such preliminary steps and could reveal complex (Kumar 2003, Kwak, Ventura & Tofang-Sazi 2000, Patil, Biradar & Jadhav 2005, R. Stojanovic, P. Mitropulos, C.Koullamas, Y. Karayiannis, S. Koubias & G .Papadopoulos 2001). For this reason, when in an industrial process time constraints play an important role, a hardware solution of the abovementioned methods can be proposed (R. Stojanovic, P. Mitropulos, C.Koullamas, Y. Karayiannis, S. Koubias & G .Papadopoulos 2001), but such kind of solution implies a further design effort which can be avoided by considering Cellular Neural Networks (CNNs) (Chua & Roska 2002).

Cellular Neural Networks have good potentiality to overcome this problem, in fact their hardware implementation and massive parallelism can satisfy urgent time constrains of some industrial processes, allowing the inclusion of the diagnosis inside the production process. In this way the defect detection method could enable to work in *real time* according to the specific industrial process.

BACKGROUND

Cellular Neural Networks consist of processing units $C(i, j)$, which are arranged in an $M \times N$ grid, as shown in Figure 1.

The generic basic unit $C(i, j)$ is called cell: it corresponds to a first-order nonlinear circuit, electrically connected to the cells, which belong to the set $S_r(i, j)$, named *sphere of influence of the radius r* of $C(i, j)$. Such set $S_r(i, j)$ is defined as:

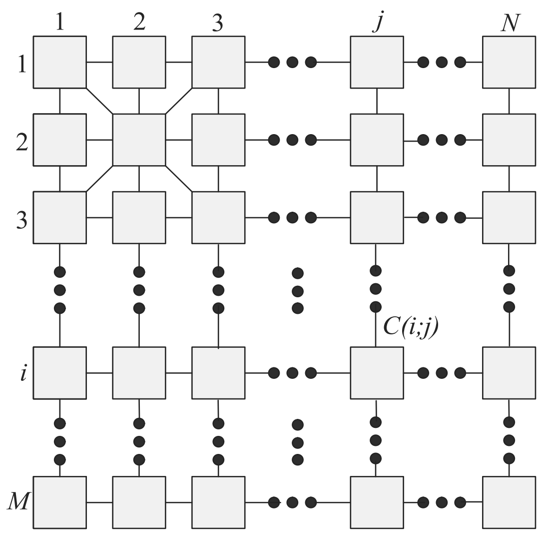
$$S_r(i,j) = \left\{ C(k,l) \Big| \max_{1 \le k \le M, 1 \le l \le N} \left(|k-i|, |l-j| \right) \le r \right\}$$

An $M \times N$ Cellular Neural Network is defined by an $M \times N$ rectangular array of cells $C(i, j)$ located at site (i, j), $i = 1, 2, .., M$, $j = 1, 2, \ldots, N$. Each cell $C(i, j)$ is defined mathematically by the following state and output equations:

$$\begin{cases} \dfrac{dx_{ij}}{dt} = -x_{ij} + \displaystyle\sum_{C(k,l) \in S_r(i,j)} A(i,j;k,l) y_{kl} + \sum_{C(k,l) \in S_r(i,j)} B(i,j;k,l) u_{kl} + z_{ij} \\ y_{ij} = \dfrac{1}{2} \left(|x_{ij} + 1| - |x_{ij} - 1| \right) \end{cases}$$

where $x_{ij} \in \Re$, $y_{ij} \in \Re$ and $z_{ij} \in \Re$ are state, output and threshold of cell $C(i, j)$, $y_{kl} \in \Re$, and $u_{kl} \in \Re$ are output and input of cell $C(k, l)$, respectively. $A(i, j; k, l)$ and $B(i, j; k, l)$ are called the *feedback* and the *input synaptic operators* and uniquely identify the network.

Figure 1. Standard CNN architecture



The reported circuit model constitutes a hardware paradigm which allows fast processing of signals. For this reason, in the past CNNs were considered as an useful framework for defect detection in industrial applications (Roska 1992). Successively different CNN-based contributions working in *real time* and aiming at the defect detection in the industrial field have been proposed (Bertucco, Fargione, Nunnari & Risitano 2000), (Occhipinti, Spoto, Branciforte & Doddo 2001), (Guinea, Gordaliza, Vicente & García-Alegre 2000), (Perfetti & Terzoli 2000). In (Bertucco, Fargione, Nunnari & Risitano 2000) and (Occhipinti, Spoto, Branciforte & Doddo 2001) non-destructive control of mechanical parts in aeronautical industrial production is carried out defining an algorithm which is implemented by means of CNNs entirely. These methods reveal effective, but a complex acquisition system is required to provide information about the defectiveness. In (Guinea, Gordaliza, Vicente & García-Alegre 2000) CNNs constitute the core processors of a system which realizes an automatic *inspection* of metal laminates, whereas in (Perfetti & Terzoli 2000) two CNN-based algorithms are proposed in order to detect stains and irregularities in a textile application. In both works real-time is guaranteed, but in (Guinea, Gordaliza, Vicente & García-Alegre 2000) synthesis criteria of CNN circuit parameters could reveal difficult to satisfy, whereas in (Perfetti & Terzoli 2000) such criteria are not defined.

In the following section a CNN-based method, that enables to overcome the most of drawbacks which arise in the reported approaches, is proposed.

AUTOMATIC DEFECT DETECTION METHOD

In this section an automatic method for the visual *inspection* of surface *flaws* of *manufactures* is proposed. This method is realized by means of a CNN-based architecture, which will be accurately described in the companion chapter (Fornarelli & Giaquinto 2007).

The suggested approach consists of three steps. The first one realizes a *preprocessing* stage which enables to identify eventual defected areas; in the second stage the matching between such pre-processed image and a *reference image* is performed; finally, in the third