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Subjective measurement of cosmetic defects using a Computational Intelligence approach

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ABSTRACT

This paper presents a Computational Intelligence scheme to deal with subjective human inspection tasks in the industry that are subjective measurements. The scheme is used to solve two cosmetic subjective measurements tasks, classification of cosmetic defects and detection of non-uniform color regions in a translucent film. The first problem is solved with two approaches supervised and unsupervised Artificial Neural Networks. Both techniques yield the same performance, 92.35% of correct classification. Considering that a human inspector has a performance between 85% and 90%, the performance achieved is acceptable. The second problem is faced with a hybrid system based on fuzzy clustering and a Self-Organizing Map. The hybrid approach involves management of uncertainty through fuzzy theory and unsupervised training supported by the SOM. The proposed system is able to find non-uniform color regions with better resolution than a human inspector. The system also showed to be more sensitive than a simple fuzzy clustering approach.

1. Introduction

Computational Intelligence (CI) is a new paradigm that provides intelligence to systems and machines. Nowadays, CI is a relatively new field that integrates several synergistic areas that have an impact on machine intelligence (Fogel and Robinson, 2003). Two of the most prominent areas that are part of CI are Artificial Neural Networks (ANN) and Fuzzy Logic (FL). Neural networks models date from the work of McCulloch–Pitts model in 1943. However, the boost of this area is related to the 1980s where we found works like the backpropagation algorithm by Werbos (1994). Fuzzy logic theory was proposed by Professor Lotfi Zadeh in the 1960s (Zadeh, 1965), but the takeoff of this area starts also in the 1980s. The cut edge in the theory of these areas report works in unimaginable topics like, intuition, imagination, and creativity (Duch, 2007; Li et al., 2003; Foo, 2000; Yu-Jia and Ding-Li, 2009). As we are aware, a huge progress has been reached in neural networks and fuzzy logic theories, and it is expected that new theories will be developed in following years. However, this progress in theoretical aspects requires an adequate balance between theory and applications.

Our motivation in this paper is to address real world applications based on neural networks and fuzzy logic to provide justification on keeping a balance between the theoretical research and real world applications on these two fields. The contribution of this work is to present how CI can simulate human behavior in quality subjective inspection tasks in industrial environment using visual information. Another contribution is a novel automatic determination of the number of clusters in the fuzzy neural model proposed in the paper.

The paper addresses the situations of how to deal with subjective measurements implicit in inspection tasks. In industrial environments, these types of tasks are generally achieved by human inspectors. In this type of inspection, the quality of a product is defined by the appreciation of a specific property of the product by the human inspector like, surface features (Wiltschi et al., 2000), shape description (Chacon-Murguia et al., 2009), bottle finish inspection (Duan et al., 2007) ripeness (Kosak Polder et al., 2002), skin color (Vezhnevets et al., 2009), shape description texture analysis (Boukouvalas et al., 1999; Ferreira et al., 2009), automatic micromanipulation technologies (Zhang et al., 2009), manipulation hand–eye for generating calibration parameters (Motai and Kosaka, 2008), fabric inspection (Sari-Sarraf and Goddard, 1999; Cho et al., 2005; Hong-gang and Jun, 2009), etc. The decision about the quality of the product is obtained by the human inspector based on a *measurement* of the aspect of the product property. *Measure* in this case, means perception or appreciation of such property. Therefore, the process involves a high degree of subjectivity (Takemae et al., 2000). This kind of inspection usually represents a great point of controversy between the production and the quality departments, and this

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controversy results in negative economical consequences for the company.

The work presented in this paper deals with two inspection tasks, the first one is related to the classification of two cosmetic defects found during the fabrication of ophthalmic lenses. The second one concerns the detection of non-uniform color regions in translucent film used in the fabrication of polarized lenses. According to our knowledge, there are no identical works reported in the literature. This may be because the problem covered in this paper is a real world problem or because other companies that have worked in these problems do not wish to release the information, which in turn makes this paper an important contribution for the industrial community. The closer work related to the cosmetic defects on lenses is reported briefly in Curran (1997) and it is reported only from a communication point of view. With respect to the topic of the detection of non-uniform color regions in translucent film, the most related work found is the researcher on the "cooking curve" (Hamey et al., 1998).

The design of vision systems able to work on these kinds of tasks is a promissory field to experiment with new vision and pattern recognition techniques. By their natural characteristics, uncertainty management, learning and generalization, evolution, etc. Computational Intelligence techniques represent an interesting alternative in the design of such vision systems. Furthermore, there may be situations where the complexity of the task requires the fusion of the advantages of neural networks and fuzzy logic. The hybrid approach incorporates the benefits of a better uncertainty management with fuzzy logic (Zadeh, 1996), and the learning and generalization characteristic of neural networks (Egmont et al., 2002; Cao and Lin, 2008; Li and Hori, 2006).

This paper presents, in Section 2, the definition of a Computational Intelligence model with neural networks and fuzzy logic oriented to the solution of industrial application inspection tasks. In Section 3, the model is illustrated in the solution of two problems, recognition of cosmetic defects presented in ophthalmic lenses and detection of non-uniform regions on translucent film. Finally, the results and conclusions are discussed in Section 4.

2. Computational Intelligence model

In this section we try to formalize a Computational Intelligence scheme based on fuzzy logic and/or ANN for subjective inspection tasks in industrial applications. The general function achieved by a human inspector may be defined by

$$H(l) : O \Rightarrow D = \{A,R\} \tag{1}$$

where $H(l)$ is a mapping function of l, product property definition measured by perception, that maps a product O to the set D with elements, accepted A, rejected R. $H(l)$ can be decomposed into two functions

$$H_{ms}(l) : O \Rightarrow \mu_l(O) \quad \text{and} \quad H_{mA}(l) : \mu_l(O) \Rightarrow D \tag{2}$$

where $H_{ms}(l)$ maps the product O into a degree of satisfaction of the property l. Finally, the function $H_{mA}(l)$ maps this degree of satisfaction to A or R.

Considering the Computational Intelligence scheme, the previous functions can be represented by the following functions. The general function is similar to (1) but now $H(l)$ is achieved through the following functions:

$$S_1(l) : O \Rightarrow \mathbf{X} \tag{3}$$

$S_1(l)$ is a feature extraction function that maps the product property into a feature vector $\mathbf{X}$

$$S_2(l) : \mathbf{X} \Rightarrow \mu_l(\mathbf{X}) \tag{4}$$

$S_2(l)$ maps the feature vector $\mathbf{X}$ to a degree of satisfaction, $\mu_l(\mathbf{X})$, of the property l. Finally $S_3(l)$ maps that satisfaction degree to A or R

$$S_3(l) : \mu_l(\mathbf{X}) \Rightarrow D \tag{5}$$

$S_1(l)$ and $S_2(l)$ can be considered as the perceptual functions achieved by the human inspector. $S_2(l)$ and $S_3(l)$ can be incorporated into fuzzy, ANN and/or fuzzy-ANN schemes as follows:

$$S_2(l), S_3(l) = \begin{cases} f_R(\mathbf{X}) \Rightarrow DOF \text{ or } f_C(\mathbf{X}) \Rightarrow \text{Centroid}, \\ A_S(\mathbf{X}) \Rightarrow \text{Hyperplane or } A_{US}(\mathbf{X}) \Rightarrow \text{Set of neurons} \end{cases} \tag{6}$$

where f_R represents a fuzzy rule system, DOF stands for the degree of fulfillment. f_C is a fuzzy clustering algorithm. A_S is a supervised ANN, and A_{US} is an unsupervised ANN. In the next section, two inspection problems solved with Computational Intelligence are presented. The methodology applied follows the CI model presented in this section.

3. Cosmetic defect classification presented in ophthalmic lenses

3.1. Cosmetic defects and feature vector definition

Two of the defects with the highest probability of occurrence during ophthalmic lens fabrication are the CF and FP defects. The CF defect is generated by textile particles that fall into the molds of the lens during the fabrication process. The FP defect is generated by chemical reactions between the polymer used to fabricate the lens and unknown particles during the fabrication process. Illustrations of these two defects are shown in Fig. 1a and b. The defect images were acquired with a vision camera with a

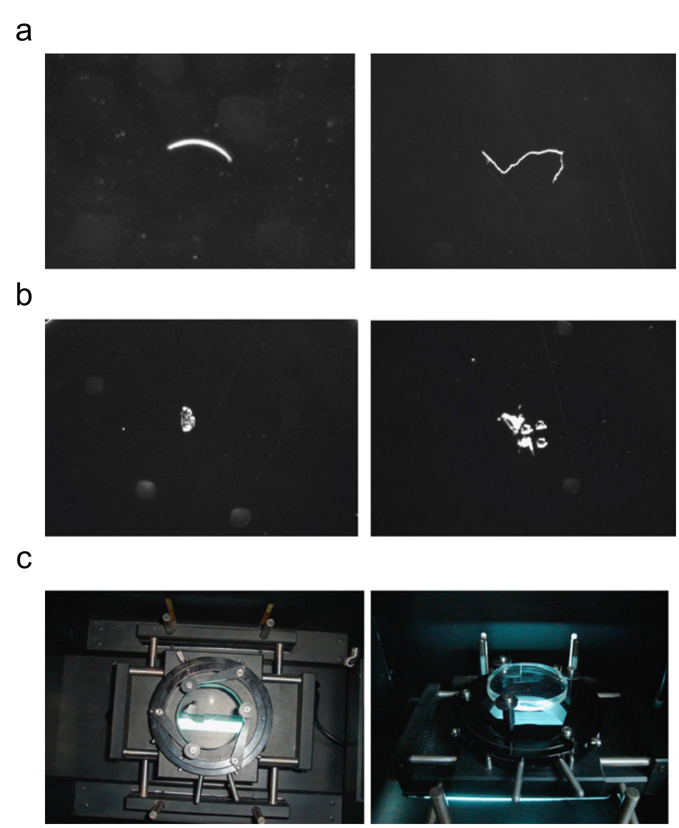

Fig. 1. Illustration of: (a) CF textile particles, (b) FP unknown particles defect examples, and (c) workstation for image acquisition.