Computational Intelligence in Industrial Quality Control

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Abstract **– The aim of the quality control in industrial application is to analyze and monitor the quality of industrial manufacturing activities. Signal processing systems and automatic visual inspection systems, which are automatic systems that perform visual inspection by means of machine vision, can play a fundamental role in quality assessment since they can guarantee a high and constant non invasive quality inspection. In the literature a comprehensive analysis of the quality control in industrial applications is not available but several ad-hoc solutions can be found. The solution of quality control problems requires being able to tackle problems of different scientific areas (signal acquisition, signal preprocessing, feature selection and extraction, data fusion and classification). The research efforts led to the development of methodologies that try to integrate all the above activities to design intelligent signal and visual inspection systems for the quality control using. Computational intelligence techniques have been recognized in the literature as a good tool which can be used by the designer to achieve these goals.**

Keywords ***– Computational intelligence, Fuzzy logic, Neural networks, Quality assessment, Quality control, Soft computing.***

I. Introduction to the Quality Control Problem

The quality control in industrial applications aims to monitor and guarantee the quality of industrial production processes. Inspection of products on high speed manufacturing lines is boring, repetitive, exhausting and dangerous for human operators. Unlike people, a computer does not get tired or bored looking at or measuring the same item thousands of times a day. Automatic quality control systems can be the key to solve such a kind of application problems, allowing an accurate, often non invasive and standardized quality control of the processes.

In the field of quality control, the presence of sensors capable to acquire data (signals or images) to be used in the monitoring of industrial processes is one of the key aspects of the design of quality control systems. The monitoring of the quality can thus make use of signal measurement or machine vision systems to allow a standardized and non-invasive control of industrial production processes.

The second element which is playing an even more important role in this research field is the family of computational intelligence techniques: the techniques based on the usage of neural networks, fuzzy systems and evolutionary computation algorithms. The computational intelligence techniques offer new methods to make smarter, adaptive and intelligent the traditional signal processing systems and visual inspection systems. Secondly, the computational intelligence methodologies can help the designer to synergically compose quality control system modules in order to obtain more accurate and performing systems.

At the best of our knowledge, a comprehensive design methodology of the quality control systems in industrial applications which can suitably exploit traditional signal processing systems, vision-based systems and intelligent systems for classification/measurement is not available in the literature. Many manufacturing industries have been able to use signal processing and machine vision systems to perform tasks such as product inspection. Nevertheless the quality control problem is still a rather unexplored research field and in the literature a comprehensive analysis of the problem is not available. The problem of quality control was always tackled by solving specific problems. Several ad-hoc solutions can thus be found in the literature [16-20]. The main industrial fields that consider the use of the quality control are software engineering, video and image compression, electric power delivery, and speech coding and speech synthesis systems.

The main difficulty to solve the quality control problem consists in the need of being able to tackle problems of different scientific areas: the data acquisition (signal or image) requires knowledge of instrumentation and measurement systems, while the data preprocessing requires knowledge of

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image and signal processing. The proper quality control activities require knowledge of feature extraction, sensor fusion, system modeling and monitoring, data analysis and classification techniques. The research efforts led to the development of methodologies that try to integrate all the above activities to design visual inspection systems for the quality assessment.

II. Quality control in industrial applications

As presented in the previous section the need to monitor industrial production processes is becoming more and more important. The quality control systems aim to analyze and judge the quality of industrial manufacturing activities but these kinds of activities involve toilsome and repetitive tasks for the process control. The quality of the human visual inspection is thus typically subject to a progressive degradation to the visual fatigue and inattention.

Recently the availability of reliable and visual acquisition devices and of high computing power hardware led to take into consideration the joint use of computers and machine vision for a non-invasive visual inspection. Machine vision allows a computer to analyze video data (such as that from a video camera) and make decisions about what it “sees”. The automatic systems that perform visual inspection by means of machine vision are called automatic visual inspection system [1]. These systems can play a fundamental role in quality control since they can guarantee a high and constant non invasive quality inspection. Reliable and high performance acquisition devices and microprocessors are nowadays available at low cost and the development of quality control systems is thus mainly limited by the capability of analysis and judging by the automatic inspection system (and not by the available hardware).

The design of a general quality control system must consider the following basic activities:

A. *acquisition* of data (signals or images) from sensors;
B. *preprocessing* of data in order to reduce the noise, compensate biases, correct aberrations in the images, enhance the signals, etc.;
C. *processing features* from the signal of important information concerning the quality evaluation (feature extraction);
D. *extraction/selection* and *composition/fusion* of the extracted features in order to better measure, describe and details the phenomena associated to the quality control problem;
E. *classification* of the occurred situation in classes defined by the designer or production of a *measure* or an *index of quality*.

Hence the solution of quality control problems implies the need to manage techniques of different scientific areas: data acquisition, data preprocessing and enhancing, feature extraction and selection, data fusion, approximation, and classification.

All the classification techniques presented in this paper can be grouped into: computational intelligence and conventional techniques. Computational intelligence techniques can be used into intelligent processing systems to solve complex problems by mimicking the human reasoning (such as neural networks, fuzzy logic, genetic algorithms, and expert systems). Conventional algorithmic techniques are not able to learn from experience but can guarantee extreme power and efficiency in solving applications. The choice of a computational intelligence or conventional technique might be in many applicative cases the optimal solution for a sub-problem, but in general not sufficient enough to solve the whole problem. As we will see in section II.E, the solution to the whole problem generally encompasses the use of both computational intelligence and conventional techniques.

In the following we describe how the basic functionalities of a quality control system can be achieved or enhanced by using computational intelligence techniques.

A. Computational intelligence for sensors

The data acquisition (signal or image) is a typical problem of instrumentation and measurement systems. The literature concerning how the computational intelligence techniques can enhance the functioning and the usage of sensor is very wide. For example, there are available techniques for sensor enhancement, sensor linearization, sensor diagnosis and sensor calibration (static and dynamic) [27]. The sensor modules can hence be more intelligent since they can self-calibrate and the undesired non-linearities can be reduced. Errors and faults can be better identified and, in case, be corrected. In particular, the automatic visual inspection underlies to the principles of image acquisition. A review can be found in [2], while an overview of the digital cameras and electronic color image acquisition devices can be found in [3].

B. Signal preprocessing and feature processing

Signal preprocessing aims at correcting and enhancing the errors occurred in acquired data due to the acquisition devices. The *features processing* is the activity which allows to extract from the input signals a set of features which will be exploited by subsequent modules of the quality control system to execute the classification/measurement of the quality.

The preprocessing of a signal mainly aims to reduce the noise and to exploit the inherent information carried by the signal. Many conventional signal preprocessing techniques can be found in the literature [38] and [39]. Not only conventional but also computational intelligence techniques have been exploited for signal preprocessing. A good review of neural and fuzzy techniques for signal preprocessing can be found in [40].

In case of images, the preprocessing aims at correcting errors due to image acquisition and non ideal source image conditions. Every system that implements machine vision functionalities requires a preprocessing phase that corrects image acquisition errors or enhances some characteristics for the visual inspection. A wide broad of image preprocessing (or prefiltering) methods and techniques is available in the literature [5-7].

In order to extract from incoming signal *features of interest* from specific patterns superimposed to their background, typically, the designer uses the physical and a-priori knowledge of the observed phenomena. The intent is to produce features from sensors that can help the system to make measurements and/or sound and reasonable decisions about the category of the patterns. For example, we can extract from an acoustics sensor particular energies in the spectrum of the sensed signal in order to measures the presence of cracks during the production of products. Otherwise, we can consider the variation of the gray level intensity in a region of interest or of an image in order to estimate the roughness of the selected surface. The literature of the Instrumentation and Measurement community concerning those issues is very wide and examples can be found in [34] and [35].

The *image feature processing* is the process of computing the features of images. A wide literature about the image feature processing can be found and, even in this case ,computational intelligence techniques can be considered [8-10].

C. Feature extraction and selection

Once the designer fixed all the features that will be processed from sensors, it is important to decide how to use them in order to obtain the quality decision/measurement. For example, not of all of them can be necessary. The main reason to keep the dimensionality of the pattern representation (the number of features) as small as possible is to reduce the computational complexity of the system On the other hand, a reduction in the number of features may lead to a loss in the discriminant power that lowers the accuracy of the resulting quality control system. A limited yet salient feature set simplifies both the pattern representation and the classifiers structure that consequently will be faster and will use less memory.

Moreover, a small number of features can alleviate the "curse of dimensionality" problem when the number of samples in the available dataset is limited [33]. The course of dimensionality problem refers to the requirement that the number of samples per feature increases exponentially with the number of features to maintain a given level of accuracy of the system. In other words, the more features will be used in the system, the larger must be the training dataset used to train the computational intelligence modules (for example the neural networks-based modules).

This important phase of the design of the quality control system is the *feature extraction* and *selection*. Very commonly, feature extraction precedes feature selection. The sequence of the two phases, whatever the order, represents a *dimensionality reduction phase*: the dimension of the final dataset is reduced, and therefore will be reduced the complexity of the computational intelligence module under training.

Even if in literature the terms selection and extraction of features are used interchangeably, they have different definitions. *Feature selection* refers to algorithms that select the best subset of the input features set. Conversely, the methods that create new features based on transformations or combinations of the original feature set are called *feature extraction* algorithms [3]. Feature extraction methods create new features based on transformations. The literature concerning these algorithms is very wide, i.e., Principal Component Analysis, Linear Discriminat Analysis, Independent Component Analysis, Kernel PCA, PCA network, Nonlinear PCA, Feed-Forward Neural Networks, Nonlinear autoassociative network, Multidimensional Scaling, Self-Organizing Map (MAP). A good review of those methods is in [21].

The *feature selection* algorithms, given a set of d processed features, select the appropriate subset of size m that maximizes the selection criterion that leads to the smallest classification error processed on the available dataset. Feature selection is dependent on the specific classifier that is used, and the sizes of the training and test datasets. Very commonly, the exhaustive search of the best subset m is almost impossible even when small dataset and d values are considered, because the number of classifiers to be tested is equal to the number of possible combination of subsets of features. In the literature many variations and improvements of the exhaustive search are presented with respect to the computational complexity of those algorithms [21].

D. Computational intelligence for data fusion

Computational intelligence techniques can be used to properly fuse the available features/sensors signals in order to obtain more significant and meaningful information concerning the quality of the observed industrial process.

The first technique is called *sensor fusion*. Sensor fusion merges information from several sensors, possibly of different type, to create new combined measurements. The computational intelligence algorithms are commonly used in sensor fusion, and a very broad literature is available [28-31], where neural networks play a fundamental role.

Computational intelligence can be exploited also to create the so-called *virtual sensors*. The virtual sensors are systems capable to measure quantities without direct sensing the measured quantity, when direct sensing is not technically feasible or convenient by using indirect techniques, or incase of the desired quantity is difficult to be measured while other strictly related quantities can be measured. For example, we can create a "crispness" sensor for owned foods by intelligently compose direct measurements coming from the oven (i.e., temperatures) and images of the cooked products. The computational intelligence techniques have been used to enhance and "virtualize" a great variety of sensors: image sensors, artificial retina/odor/cochlea sensors, visual sensors, taste sensors, tactile and roughness sensors [27].

Very interesting techniques can be found also to intelligently collect data from networks of sensors [37].

Recent advances in the literature proposed interesting solutions concerning the multi-sensor data fusion and its application to industrial control [22] and [26] also by the methodological point of view [23-25]. Data fusion systems can be also composed by many different heterogeneous modules, for example sensors, data-fusion nodes, data-fusion databases, and expert knowledge databases.

E. Computational intelligence for classification and measurement of the quality

In this activity, the designer aims to produce a module that receives in input all the selected features and provides in output a value associated to the *classification* of the quality (an integer) or an *index of quality* (a floating point value).

The classification can be considered as the problem of partitioning the feature space into regions (one for each class). Ideally the classifier should take always correct decisions without ambiguous classifications or errors, but in practice we aim to reduce (or minimize) the classification error.

As presented in section II, the classification approach can be conventional or based on computational intelligence. The conventional algorithms guarantee power and efficiency in classification applications, but they are not able to learn from experience (examples) [21]. Computational intelligence techniques for classification encompass statistical approaches [11], neural networks [12] and fuzzy classifiers [13]. As explained in section II these techniques allow mimicking the human reasoning by generalizing a behavior learnt during a training phase. For this reason the computational intelligence techniques overcome the need to have e a formal description of the problem. In fact when the formal description is not available, the model is fully or partially inferred by exploiting a finite number of examples [21].

The computational intelligence techniques are thus capable to learn input/output mapping from examples (inductive learning). For this reason, each module of the system that will implemented by computational intelligence techniques, must be associated to a *dataset of input/output sample*s that will be used to train the computational intelligence modules. The term "train" refers to the learning algorithm that will fix the parameters of the model using the available dataset. For example, the weights of a neural network will be tuned in order to minimize its output error on the training dataset. The available dataset is commonly partitioned in *training* and *validation* set.

Besides we must consider that computational techniques, such as neural networks and fuzzy logic, can provide solutions with low computational complexity to complex problems. This peculiarity can play a very important role when real-time or low-consumption requirements are present.

When both soft-computing and conventional techniques are present and cooperate in a processing system, the system is named *composite*. The joined use of conventional and computational intelligence techniques in a processing system can provide systems which better satisfies the requirements of the designer (in terms of accuracy of system behavior, computational complexity or robustness) with respect to others system composed only by conventional or soft-computing components [34,35]. The problem of composite system design is widely tackled in the literature and a methodology for composite system design is presented [15].

Furthermore, in case of classification application, we must also keep into account that two different classification philosophies are suggested in the literature: *closed world* and *open world* classification [14]. The closed world classification aims at classifying samples according to a set of pre(user)-defined classes, while in open world classification the classifier either classifies the sample as belonging to a known class or creates a new class.

It is interesting to note that open world classifiers can guarantee higher flexibility than closed ones since they are able both to classify known samples into existing classes and to introducing new ones. This approach overcomes the limits of the closed world classifiers to fix the class set during the training (and no changes can be performed during the operational life).

Neural networks can be again considered when the desired output value should not be an integer -as in the case of classification- but it is required a "countinuos" index of quality (i.e, floating point values). The well-known capability of neural networks to learn any input/output mapping (given a sufficient number of hidden neurons) with generalization capability [32], can be exploited by the design to implement the relationship between the input features and a desired index of quality based of available examples.

F. Computational intelligence for system optimization

During the design activities, the modules composing the quality control system can contains parameters (i.e., thresholds, filters coefficients, number of hidden neurons in neural networks) which can not be easily fixed, since they mutually interact in very complex manner each others affecting the overall behavior of the system (i.e., final accuracy, computational complexity, maximum possible throughput, memory occupation). Very often, the designers use *trial-and-error approaches* to fix those parameters, reaching sub-optimal solutions since it is typically impossible to exhaustively explore the parameters 'design space due to its dimensions.

The literature shows that the *evolutionary computation* techniques can help to solve this complex optimization task. In this case the vector of parameters to be optimized can be considered as a genome of the quality control system. Then, a benchmark set of input data must be chosen in order to test each candidate system that will be proposed. The output of the quality control system using such a benchmark dataset is used to produce the so called *fitness function* of the system. Typical fitness function can be the *classification error* of the system (obtained using the benchmark dataset), or an *error function* based on the distances between the expected output and the real output of the system.

In this situation, we can exploit a *genetic optimization* algorithm in order to find the best parameters vector which minimizes the error function over the chosen benchmark dataset. First of all, the genetic algorithm will produce an initial population of individuals (individuals characterized by different vector parameters), typically by random procedures. Then, for each individual, its fitness function is processed. Only the individuals with best fitness functions can participate to reproduction: selected couples of individuals will generate a new individual with a genome composed by a genomic crossover operation between the parents. Random mutations of the population genomes can also happen (random variation of the vector coefficients). This procedure, called *epoch*, is iterative repeated till a termination condition occurs, obtaining the strategy called "the survival of the fittest".

A very broad literature describes this family of optimization algorithm as capable to efficiently explore very large parameters space, without get stuck of local minima of the error function during the design space exploration [36].

The proposed computational intelligence method can also greatly help the designer in a *global fine tuning* of the system. In this case the initial population of candidate systems is not randomly created, but it can be created by solutions produced by the designer.

III. CONCLUSIONS

The solution of quality control problems requires being able to tackle problems of different scientific areas (signal acquisition, signal preprocessing, feature selection and extraction, data fusion and classification). The research efforts led to the development of methodologies that try to integrate all the above activities to design intelligent signal and visual inspection systems for the quality control. The computational intelligence techniques offer suitable solutions to the designer to enhance the basic modules of a quality control system and intelligent compose available information in order to obtain more accurate, adaptive and performing systems.

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