Computational Intelligence for Industrial and Environmental Applications

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***Abstract*—Computational Intelligence (CI) techniques are being increasingly used for automatic monitoring and control systems, especially regarding industrial and environmental applications, due to their performance, their capabilities in fusing noisy or incomplete data obtained from heterogeneous sensors, and the ability in adapting to variations in the operational conditions. Moreover, the increase in the computational power and the decrease of the size of the computing architectures allowed a more pervasive use of CI techniques in a great variety of situations. In this paper, we propose a brief review of the most important CI techniques applied in each step of the design of a monitoring and control system for industrial and environmental applications, and describe how these techniques are integrated in the development of efficient industrial and environmental applications.**

***Keywords*—Computational Intelligence, Neural Networks, Industrial monitoring, Environmental monitoring, Control system.**

I. Introduction

CI techniques represent enabling technologies for the design of innovative intelligent systems for industrial control and environmental monitoring. In fact, traditional systems are often based on physical models or statistical analysis, designed by experts of the field. In case of complex phenomena and processes, these models might not be easy to devise and might be incomplete or inaccurate. Moreover, changes in the observed processes (e.g. due to the machinery aging or updates of manufacturing specifications) often require manual adjustment of the monitoring and control systems. Noisy data acquired in non-ideal conditions can also increase the complexity of designing and applying mathematical models in real scenarios.

Differently from traditional monitoring and control methods, under proper conditions, CI techniques allow to learn the desired behavior of the system from examples, adaptively updating their knowledge during system operation, mitigating the negative effects of noise data, and reducing costs and efforts needed to design and maintain the system. In fact, thanks their robustness to data noise, examples of suitable CI techniques for industrial and environmental applications are artificial neural networks, fuzzy logic methods, Support Vector Machines (SVM), and evolutionary algorithms [1].

The number and variety of scenarios in which monitoring and control systems based on CI are used is constantly growing, thanks to the continuous increasing of computational resources and size decreasing of computing architectures. Examples of applications in industrial scenarios are quality control [2], robot control [3], production monitoring [4], and detection of machinery faults [5], [6]. In environmental applications, CI techniques are mostly used to forecast [7], [8] and monitor [9] physical phenomena.

Despite wide differences in application scenarios, monitoring and control systems share the same basic architecture (Fig. 1). They are composed by the following modules: acquisition sensors, preprocessing of the acquired data, feature extraction and selection, data fusion, estimation of the class or continuous values describing the evaluated phenomenon. In the literature there are studies that apply CI techniques in each module [10], [11]. Moreover, there are methods that use CI to optimize the performance of existing systems [12], [13].

This paper presents a brief review of recent advances in CI applications for environmental and industrial scenarios. In particular, we first present an overview of applications of CI techniques in such contexts. Secondly, we propose an analysis of the literature on CI methods designed for each component of the monitoring and control systems. In particular, this paper is organized as follows. Section II describes applications based on CI for industrial and environmental scenarios. Section III presents a design methodology for intelligent monitoring and control systems, by depicting the architecture of monitoring and control applications and showing the use of CI techniques in every module. Finally, Section IV concludes the work.

II. Applications of industrial and environmental monitoring

The increase in the computational capacity of processing architectures, as well as the decrease of their size, allows the use of automatic monitoring and control systems in numerous scenarios [14], [15]. In particular, portable general-purpose processing architectures with high computational power, battery life, and networking capabilities [16], as well as robust and long-range vision systems that can be deployed using low-cost equipment [17], [18], enable the implementation of numerous monitoring and control systems able to work also in harsh conditions, such as industrial [14] and environmental applications [15]. In this context, CI techniques have been researched in order to fuse noisy or incomplete data from multiple sensors and learn the relationship between the data

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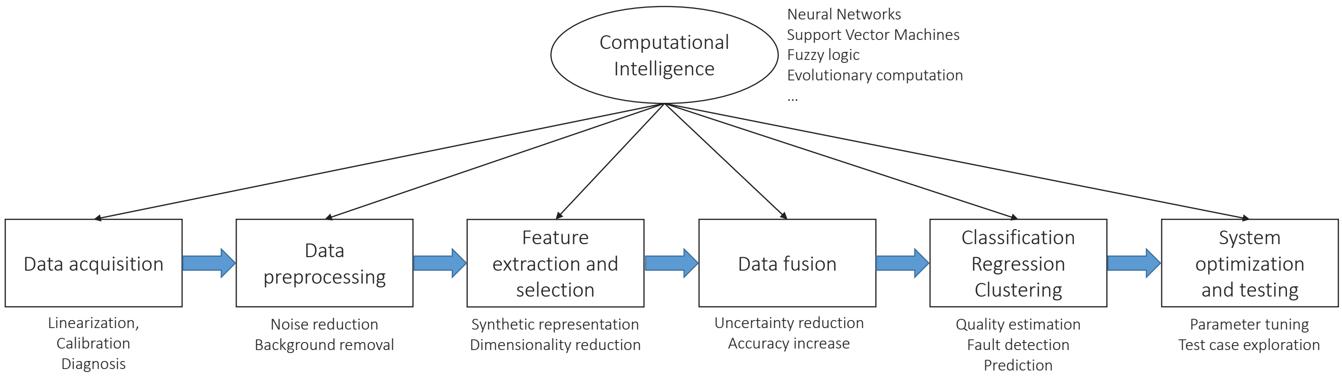

Fig. 1. Outline of an intelligent monitoring system for industrial and environmental applications

and the observed phenomenon, while adapting to different operational conditions, to increase the accuracy, reliability, and speed in detecting possible problems [2], [19].

In industrial applications, vision-based monitoring and control systems are often employed to perform a touchless, non-invasive, and non-destructive supervision of the process, and as a low-complexity alternative to the use of several sensors for measuring different characteristics of the raw materials or the final product, such as granulometry [20]–[22], volume [23], and surface defects [24]. Moreover, Wireless Sensor Networks (WSNs) are being increasingly used for industrial monitoring due to their low cost, ease of installation, adaptivity, and self-organization [6], [25]. In industrial applications, CI techniques can be used to map the features extracted from the images or from the sensors to the observed quantities [20], [21], [23], [24], and they can be used as a general approach to monitor the quality of the industrial production process, by learning the relationship between the features of the raw materials and the quality of the obtained product [26]–[31], or to detect faults in the machinery by learning from the normal operating parameters [5], [6], [32]–[34].

In environmental applications, monitoring and control systems can be broadly classified based on their architecture as centralized, distributed, or remote sensing systems [4], [15]. In particular, centralized systems include vision-based monitoring systems based on a single point of observation, which are often used in situations requiring long range detection, such as wildfire detection [35], [36]. Distributed systems composed by WSNs, on the other hand, are used for numerous environmental monitoring applications due to their self-organizing capability, long battery life, and the possibility of being deployed automatically on large spaces [19], [37]. Examples of applications include the monitoring of water quality [38]–[40], climate change [41], meteorological data [7], structural health monitoring [42]. Lastly, remote sensing systems can exploit satellite imagery for large-scale environmental monitoring of planetary phenomena, such as pollution [9], [43], weather forecasts [8], seismic activity [44]. In environmental applications, CI techniques are often used to detect the phenomenon of interest by fusing data obtained from heterogeneous environmental sensors (e.g, temperature, humidity, chemical concentration, vibrations) [19], [39], [41], [42], by classifying the distinctive features extracted from one-dimensional or two-dimensional signals [8], [9], [35], [43], [44], and by performing forecasts based on time series analysis [7], [38].

III. Design methodology for intelligent monitoring and control systems

The design of a generic monitoring and control system, applied to industrial or environmental applications, encompasses different tasks [2] (Fig. 1):

A) *Data acquisition*, e.g., signals and images;
B) *Data preprocessing*, which is performed to enhance the acquired data, by reducing noise or separating the pattern of interest from the background;
C) *Feature extraction and selection*, which is performed to obtain a synthetic representation of the raw data out of the characteristics that mostly relate to the monitoring application;
D) *Data fusion*, which is performed to reduce uncertainty and increase accuracy, by combining information from sets of heterogeneous acquisition sensors;
E) *Classification, regression and clustering* of the observed phenomenon, which is performed for quality estimation, fault detection, prediction, etc.;
F) *System optimization and testing*, which is performed to improve the overall performance, by tuning the parameters of the system or by exploring the test cases.

A. Data acquisition

The first activity of a monitoring system is data acquisition. The acquired data can be one-dimensional signals or multi-dimensional signals (e.g., images, frame sequences, or three-dimensional models).

There are sensors that acquire signals representing all the five human senses and sensors that acquire signals describing different physical quantities, such as distance, pressure, temperature, humidity, and the presence of chemicals.

CI techniques are frequently employed to calibrate the sensors [45]–[47] in order to obtain more accurate results with respect to traditional algorithms. Another application of CI techniques is the sensor fault detection [48]. In particular, most of the studies in the literature regarding this step are based on supervised learning approaches, like feed-forward neural networks [45], [46] and SVMs [47]. Some approaches are also based on fuzzy logic [49] and evolutionary algorithms [50].

B. Data preprocessing

The aim of data preprocessing is to remove the noise eventually captured during acquisition or transmission, and to enhance the quality and readability of data. In fact, sensors used in industrial and environmental applications can be affected by adverse conditions like illumination and temperature. Also, interferences in the channel used for transmission can alter the signal.

Filters can be designed to effectively improve one- and multi-dimensional signals (e.g., two-dimensional images), by reducing noise in the spatial domain or in the frequency domain (e.g., the Fourier transform of the signal). Moreover, when degradations of the signal occur, as image blur, filters can be used to restore the original signal. In this context, many CI approaches can be used to perform this kind of tasks, including neural networks [51], [52], fuzzy systems [53], evolutionary algorithms [54], or SVMs [55].

In addition, in many application domains it is necessary to perform operations to separate the pattern of interest from the background, to normalize it, and to define a compact representation [1], [56]. In the case of images, these operations are useful to enhance some characteristics of the image for human visual inspection. For instance, recent works have proposed to use neural networks to segment suitable areas for bee foraging in satellite images [57] or fuzzy methods to segment time-series in chemical processes [58] or wood particles in panel production images [20].

C. Feature extraction and selection

Data sensed and preprocessed can be represented through a set of features extracted from the data, of which the most discriminative can be selected, to produce a synthetic representation of the observed phenomenon, which can help the monitoring and control system for measurement purposes or for decision-making. Both feature extraction and selection steps have the purpose of reducing the dimensionality of the original data to limit the complexity of the problem while retaining its discriminative characteristics, allowing the use of simpler classifiers with a lower computational complexity and less prone to overtraining effects [59]. Examples of features extracted in industrial and environmental applications can be the anomalies in the frequency ranges of a signal to predict the quality of the production process [11], [26], the gray-level variations of the image used for estimating the granularity of a surface [60], and the shape of the moving area in a frame sequence to identify smoke [35].

In particular, feature extraction methods have the purpose of finding a reduced space by transforming the original feature space. In this context, traditional methods include the Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), Independent Component Analysis (ICA), Multidimensional Scaling, and polynomial approximation [1]. Moreover, CI techniques have also been used for feature extraction, including Feed-Forward Neural Networks [61]–[63], Self-Organizing Maps (SOM) [64]–[66], and deep learning [67]. Regressive models based on Radial Basis Function (RBF) Neural Networks have also been used for feature extraction [68].

Furthermore, feature selection methods perform a dimensionality reduction of the original data by selecting the subset of the extracted features producing the smallest classification error. While the exhaustive search in all possible subsets of the original feature set may be computationally impractical, suboptimal subsets of features can be obtained by methods such as the Sequential Forward (Backward) Selection and the Sequential Floating Search [1]. In this context, evolutionary algorithms have been proposed to address feature selection problems due to their global search ability [69]–[71].

D. Data fusion

The fusion of different sensor signals/features can provide a way to obtain more significant information that can be exploited to monitor and control industrial and environmental processes. Data fusion offers several advantages, such as reducing uncertainty or increasing accuracy [72]. However, it also has to face several challenges, such as conflicting data, outliers or data imperfection [73]. CI techniques can offer solutions to these challenges, for instance, by using fuzzy methods, neural networks or SVMs.

The first approach for which CI can be useful is multi-sensor fusion, in which the measurements coming from different sensors are combined to create new information. In this way it is possible to reduce ambiguity or to increase reliability, confidence and detection [73]. In industrial applications, the fusion of information coming from different sensors through neural networks can detect the wearing of tools [74]. In fact, the fusion using SVMs has demonstrated its suitability to detect motor faults [34], while neuro-fuzzy systems can be used to detect anomalies in resilient hybrid energy systems [33]. There are also many examples of applications in environmental areas. For instance, fuzzy systems have been applied to characterize landslides fusing geophysical data [75], and fuzzy systems, neural networks and SVMs have demonstrated their ability to fuse data to detect flooded areas [76].

Another area in which CI has demonstrated its utility for fusion is in WSNs. This kind of network aggregates the information of distributed autonomous devices that cooperatively monitor industrial processes or environmental conditions. CI methods can improve the robustness and flexibility of WSNs by providing adaptive methods that favor the emergence of intelligence [19]. These networks are widely diffused for environmental monitoring, for instance using fuzzy methods to aggregate temperature measurements [77], or SOMs to measure flood levels [78]. Nonetheless, there are also applications to industrial scenarios, such as, using fuzzy approaches to perform fault detection [79].

CI can also be used to create virtual or soft sensors. This kind of sensor can measure physical quantities without actually sensing the measured quantity. Virtual sensors offer interesting advantages such as lower costs, easy retuning or real-time estimation [80]. However, when a model of the physical process is not available or it is too complex, the use of CI techniques can produce adaptable models that are obtained by learning from examples. In industrial scenarios, there are many examples of virtual sensors created using CI, for instance using RBF neural networks in a chemical reactor, or neuro-fuzzy systems to monitor the safety of a hydrogen electrolyzer [81]. CI-based virtual sensors have also been studied for environmental monitoring, for instance, to find odour source localizations using a neuronal approach [82].

E. Classification, regression and clustering

The classification, regression, and clustering steps have the objective of producing a model that can discover unknown patterns in the extracted features, by classifying the samples, predicting a necessary value, or grouping them. In these steps, the use of CI techniques can provide flexible and adaptive approaches, which can work on noise-affected or incomplete data. In this way, it is possible to obtain approximate solutions, which are robust and have a limited computational complexity. In fact, CI methods can be trained using a finite number of samples [1], allowing them to mimic human reasoning and generalization. This is particularly important, since the increase in complexity of the model does not guarantee an increase in performance, and it is preferable to use simpler models [28].

In classification, a class label is given to a set of samples that are similar or share some characteristics to differentiate them from samples belonging to a different class [83]. CI techniques have been extensively applied to classification problems in industrial and environmental applications. Relevant examples include quality prediction in diverse production processes using neural networks [26], [27], evolutionary fuzzy systems [84] or SVMs [31], or fault detection using neuro-fuzzy systems [33], or SVMs [34]. Good examples of environmental applications include the use of neural networks to detect pollution problems [9], or natural disasters [35], [44].

Regression tasks try to find a function that exploits the extracted features to calculate a real value, instead of a class. This kind of task is usually necessary in environmental applications, and in this context CI techniques have demonstrated their ability to produce successful approaches. For instance, CI methods, such as SVMs, swarm methods or neural networks, have been used to predict city air quality [85] or river water quality [38], [40]. The use of CI regression in industrial applications is also widely extended, given its capability to obtain models robust to noisy or incomplete data. Many applications can be found in the literature, such as the use of neural networks, neuro-fuzzy systems or SVMs to predict energy consumption [86], quality parameters [87] or to obtain soft sensors [81], [87], [88].

Clustering permits to group similar samples together and separate dissimilar samples, without a-priori knowledge about their class. For this reason it is also called unsupervised learning. CI-based clustering algorithms offer higher flexibility than traditional methods, for instance, by permitting a sample to belong to more than one cluster. This kind of technique has been commonly applied to industrial scenarios, for example to group energy demand using fuzzy methods [89], or to predict the necessity of performing maintenance of machinery [90]. We can also find many works that apply CI clustering methods to environmental applications, such as the interpretation of seismic tomographies using neural clustering [91] or the detection of redundant information in pollution detection networks using fuzzy clustering [92].

F. System optimization and testing

The design of monitoring and control systems for industrial and environmental applications requires to combine many modules that, at the same time, contain numerous parameters. The tuning of these parameters is a complex process, because they interact in unknown ways. In most cases the traditional approach of trial and error tuning can only obtain sub-optimal solutions, because it is practically impossible to exhaustively explore all parameters combinations [2]. CI optimization techniques, such as evolutionary algorithms or Particle Swarm Optimization (PSO), can provide effective strategies to find high quality solutions to this kind of problem, even under changing conditions [93]. Recent applications of this kind of approach include the use of advanced evolutionary algorithms to optimize the parameters in milling operations [13] or the whole set of system parameters of a multigeneration energy system [12].

The testing of the different modules that compose the system is also an important task that can improve the overall performance by avoiding costly errors. In most cases, the testing is carried out by humans, because the domain of potential test cases is very large, and it is not possible to perform an exhaustive exploration. However, the lack of automation can increase the costs if the quality of the test is low and they cannot find important errors. A recent alternative consist in the application of testing techniques based on evolutionary algorithms, which have demonstrated their ability to generate effective test cases [94]. For instance, this kind of approach has been applied to test complex control systems [95], [96].

IV. Conclusions

Industrial and environmental monitoring and control systems have to deal with complex phenomena and processes, which makes their design and development a complicated task. Traditional approaches try to cope with these problems using physical models or statistical analysis. However, these models may not be easy to devise and may be incomplete or inaccurate. Furthermore, they can have problems when they have to face noisy or incomplete data. CI approaches, such as neural networks, fuzzy systems, SVMs, and evolutionary algorithms, offer a good compromise alternative, since they provide approximate solutions, which are robust to incomplete and noisy data, have limited computational complexity, and are able to adapt to different operational conditions.

This paper presented a brief review of recent advances in CI applications for environmental and industrial scenarios. In particular, we presented CI techniques that cover all the steps of the design of a monitoring and control system for industrial and environmental applications, including data acquisition, data preprocessing, feature extraction, data fusion, classification, regression, clustering and system optimization, to provide a complete design methodology for intelligent monitoring and control systems.

The proposed review illustrates the suitability of CI techniques for increasing the performance and robustness with respect to traditional approaches, and that several CI approaches can be exploited to improve the different design steps of industrial and environmental applications. We believe that recent developments in CI field, such as deep learning or hybrid systems, will gain research attention and provide new alternatives to further increase performance and adaptability.

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