Intelligent Defect Management System For Porcelain Industry Through Cyber-Physical Systems

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Abstract— **This paper presents an intelligent defect management system based on cyber-physical systems that orchestrate computational resources with physical systems in the specific environment of porcelain manufacturing. Sensors and computer vision techniques detect defects and faults, an intelligent information processing system based on ontologies and deep learning methods quantify different types of defects in porcelain products and provide information to the decision making system and actuators in the workflow. The system is developed within a project in collaboration with one of the biggest porcelain ware producer in Europe. It focuses on defect causation analysis and provide an advanced management system aiming to facilitate defect measures and rectifications by: (1) collecting and classifying defect data; (2) identifying causations of defect and analyzing its impact; (3) searching and managing defect information by means of knowledge management (KM) techniques, namely ontologies; and (4) developing agile defect control of porcelain ware. The final goal and result of the project is to achieve an intelligent and agile manufacturing system.**

Keywords — ***Cyber-physical system, defect detection, computer vision, ontology, deep learning***

I. INTRODUCTION

Defects seriously affect the performance and productivity in porcelain ware industry. Impact is measured by costs, time, materials, and manpower. Inspecting porcelain ware during the manufacturing process is an expensive process, which requires trained personnel who individually examine each dish for potential defects.

Consequently the human influence is significant and results in a low quality inspection due to human subjectivity and fatigue. An automatic system can provide many economical and safety benefits such as: to reduce human presence in a difficult environments and human error; to increase efficiency and stability in the process; to promote faster and more economic inspection.

This paper presents a real-world innovative cyber- physical system (CPS) designed to optimize and innovate the manufacturing process of the porcelain. The industrial partner (IPEC) is a leader in the European porcelain industry. IPEC has over 150 industrial FANUC and ABB robots, which are used in the processing and finishing phases using vision systems. The artificial vision or Integrated Robot Vision (iRVision) allows the robot to control positioning. At present, the company does not have an automated system for the identification, classification and remediation of defects, this process being executed by employees. The quality check of products and defect identification is performed visually and manually. For economic reasons, the improvement of quality control system is required in order to reduce production costs, operation time spans and material resources. It is necessary

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that quality control requirements should have limited effect on the costs and production times, which led to the need of finding solutions for intelligent inspection.

This paper proposes an automated inspection and management framework for the porcelain ware production by using a CPS architecture. The remainder of this paper is structured as follows: Section II describes related work; Section III proposes the CPS architecture and technical approaches such as computer vision techniques, information processing by using ontologies and deep learning methods. Section IV presents some experiments and results achieved so far, and Section V presents conclusions and future development directions.

II. RELATED WORK

Porcelain and ceramic plates may not meet the dimensional tolerances that are demanded by the manufacturer, and even if they do, defects can potentially arise on the surface of the plates themselves, including scratches, cracks, pinholes, chips, specks, small bumps that may be formed in the glaze during the firing process, welts etc.

According to the performed bibliographic research there aren't available computer vision solutions for plate inspection. In fact, the visual inspection by image processing and analysis is still an emerging technology in the global ceramic industry [1]. The tiles production sector has been one of the most prominent sector concerning the research and development of vision techniques and prototypes [2-5]. Those techniques, based on adaptive segmentation and edge detection are dedicated to identify the more relevant defects that were found to depreciate the ceramic plates. Standardization on the determination of ceramics quality has been established by the International Standard Organization (ISO) in the SNI ISO 10545-2:2010 document [6]. Defect measurement in the standard measurement are: (i) quality measurement of ceramic surface, such as cracks, crazing, unevenness, pinhole, devitrification glazes, specks or spots, blisters, and welts, and (ii) measurement of dimensions, such as length and width, straightness of side, rectangularity, and surface flatness. In many proposed techniques, most of them are to extract texture feature for detecting defect on ceramic [7], [8], and [9]. H. Elbehiery et al. [10] proposed techniques for detecting surface defects with a two steps algorithm: Step 1. Acquire clear image tiles using histogram equalization and Step 2. Detect various types of surface defects, such as crack, spot, pinhole, and blob using shape feature extraction through morphological operations. Another study proposed an algorithm to separate tiles into defect or no defect category. Separation had done by comparing the number of defect pixels on the analyzed image with the reference image. Morphological operations were then applied to the defective tile image during the defect classification process [11]. Significant efforts have been invested in defect measurement by computer vision techniques, especially for ceramic tiles. However, most of the studies refer to the identification of defects and not on the causality of such defects and flaws and analyses of impact on the production sector.

This research emphasizes the necessity of identifying causations of defects in order to prevent their recurrence and further more to provide an automated control system and inspection plans. The system includes a causation analysis to reduce defects by developing suitable feedback and feed-forward knowledge networking mechanisms. Such structure is proper to a CPS.

Cyber-physical systems (CPS) as defined by the National Science Foundation are engineered systems that are built from and depend upon the synergy of computational and physical components [12]. CPS are coordinated, distributed, and connected, and must be robust and responsive. Having such characteristics the CPS exceed the now-a-days simple embedded systems in capability, adaptability, resiliency, safety, security, and usability. Examples of the many CPS application areas include the smart electric grid, smart transportation, smart buildings, smart medical technologies, next-generation air traffic management, and advanced manufacturing [12].

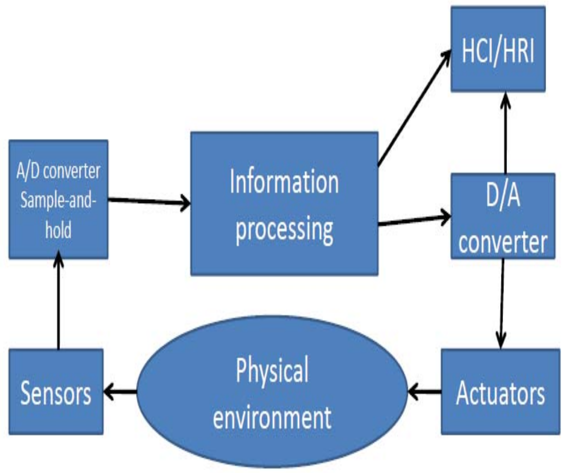

Fig. 1 CPS components [12]

CPS are reactive systems being in continuous interaction with their environment [12]. Dedicated towards a certain application, CPS are hybrid systems composed by analog and digital components. Knowledge about behavior at design time can be used to minimize resources and maximize robustness. CPS have high dynamics caused by the frequent changes of the environment and also high volume of sensored data traffic. The challenges and technology gaps are described in a *CPS Vision Statement* published in 2012 by the federal Networking and Information Technology Research and Development (NITRD) CPS Senior Steering Group [13]. New relationships between the cyber and physical components require new architectural models that redefine form and function. They integrate the continuous and discrete, compounded by the uncertainty of open environments. With the greater autonomy and cooperation possible with CPS, greater assurances of safety, security, scalability, and reliability are demanded, with focus on open interfaces, modularity, interoperability, and verification [12]. Such systems are expected to improve industrial performances in terms of agility, efficiency and re-configurability [14]. In order to achieve the improvements, cognitive abilities are needed to acquire and treat information about themselves or other CPS, and extrapolate the information to make decisions [15].

When applied in manufacturing environments, CPS are also commonly known as Intelligent Manufacturing Systems (IMS), a term which can be attributed to a tentative forecast of J. Hatvany and L. Nemes from 1978 [16]. These systems include typical elements related to artificial intelligence such as: pattern recognition techniques, expert systems, artificial neural networks, fuzzy systems [17].

In general, IMS are intended to be components which satisfy the Plug-and-Work requirements to facilitate their use. These requires a deep study around industrial communication safety [18]. Efforts are required to create correct and reliable process plans on small series production since they cannot be spread on a large number of units produced [19]. Besides, manufacturing environments are often dynamic and, therefore, they need to be adapted regularly. However, these processes are expected to achieve an improvement in the quality and the productivity of the production process [20]. Overall, the benefits of automated process are highly evident to manufacturing companies. However, a major challenge is the integration of the employees' expertise into IMS to perform correct and reliable process plans while avoiding the use of elevated individual efforts [21].

III. CPS General Architecture

In order to improve manufacturing in the porcelain ware industry this project proposes a CPS that incorporates various sensors, information processing through the development of a knowledge base (KB) using advanced concepts of computer vision (CV), ontological engineering (OE) and deep learning (DL), and finally a decision making system and actuators that use the extracted knowledge. The main purpose of this architecture is to check and/or prevent defects as a part of the workflow quality management. In porcelain ware industry, human staff identifies defects and record them with information of drawings or documents such as a checklist. Then, the collected defect data are re-documented into a computer system.
Once a defect is identified, the control manager takes various actions. To improve this routine and manual defect inspection we proposed an intelligent inspection system that enables managers to automatically record inspection contents in the site. Classification and composition of defect data have to be structured not only to figure out defect causations and impacts precisely, but also to prepare a defect management plan. More importantly, the defect classification is necessary to comply with an industry-standard information classification and also to include more detailed defect control information such as causations, cost impact, work situation and measures, control time and method, and so on. Above all, it is essential for the defect classification to consider convenience and efficiency in collecting, searching and reusing defect information.

A. System General Architecture

The architecture of the intelligent defect management system is proposed as defect classification standard methodology. The framework reflects the KM process, consisted of three phases such as: acquisition/processing, retrieval/recognition, and decision/reuse. Three inter-related solutions are proposed, all being components of the CPS: (i) 2D/3D image procession by using CV techniques, (ii) porcelain ware domain and defect-specific domain ontology development, (iii) and intelligent defect management by multi-agent systems and robots. The conceptual system framework and the solutions are illustrated in Fig. 2.

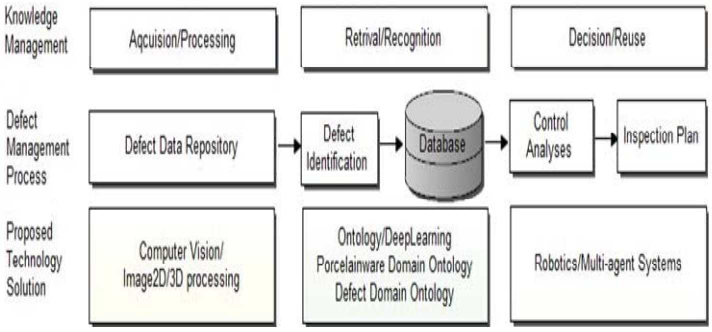

Fig. 2 CPS for the Intelligent Defect Management in Porcelain Industry

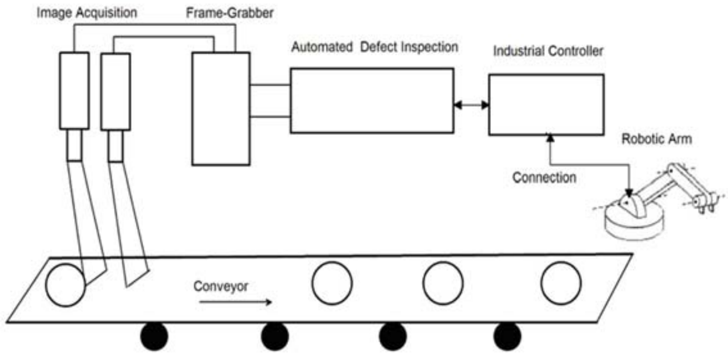

Fig.3 Defect Detection through CPS in the Workflow

The optimized system will be integrated in the production flow as follows:

Step 1. The product reaches the inspection system.
Step 2. Sensors detect the product and send signals to the vision system under optimal lighting conditions.
Step 3. The artificial vision system receives data from sensors.
Step 4. Software algorithms process and analyze the received image.
Step 5. Industrial controller sends signals to an actuator / robot that acts as a diverter if the product is defective.

B. Sensors and image processing techniques

The artificial vision or Integrated Robot Vision (iRVision) allows robot control for easy positioning and fault detection.

Image acquisition and image processing is currently achieved by the robot controller. IPEC uses IRVision only in the 2D version, with SONY XC 56 cameras. The iRVision software integrates GPM *Locator Tool (Geometric Pattern Matching)* that compares the model of the captured image to the reference model. Depending on the score, scale and contrast it decides whether or not these 2 models coincide. 3D Sick IVC cameras are used for pick & place applications on moving conveyors. Image acquisition and processing is done by the camera and the information is sent to the robot. Both 3D cameras and robots are connected to an encoder - mounted on the conveyor - to retrieve its speed.

Fig. 4 presents two types of defects, namely *chips* and *scratches* that have been identified in the images by using image processing techniques.

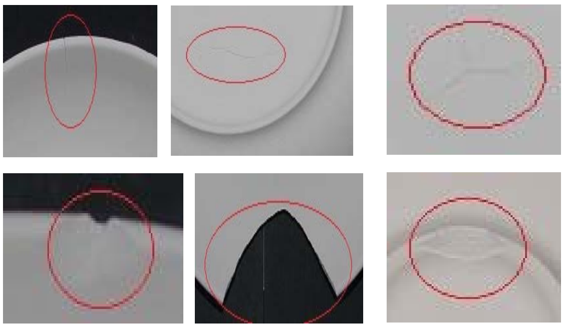

Fig. 4 Defects in porcelain ware. Chips and scratches

Further on, images are stored in a database and analyzed on the basis of a taxonomy developed by using ontologies.

C. Ontologies

An ontology provides a formal representation of a domain knowledge, through concepts, relationships, axiomatic constraints, and individuals [22]. Fig. 5 represents a part of the Defect type domain that was used in our experiments.

The defects are classified in the defect type ontology (see Fig. 5)

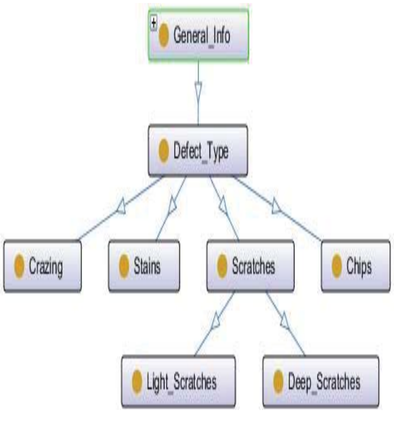

Fig. 5 View of the Defect Type Ontology

It contains a set of concepts for defect types in porcelain ware image database, and relations between the concepts. Using the domain ontology, we proposed an Ontology Based- Deep Restricted Bolzmann Machine (OB-DRBM) model [23] to learn a set of representations, each of which corresponds to a concept in the defect type ontology. This set of representations learns to encode regularities from data with various semantic granularities for the current domain.

The architecture design of the OB-DRBM model primarily uses a set of classes *C* and properties *P* in a domain ontology following the subclass relations in P. For concepts c, s $\in$ C, we use subclass (c, s), superclass (c, s) $\in$ P to denote the subclass and superclass relations between c and s. For each c $\in$ C, $\pi(c) = \{s \mid superclass(s, c), s, c \in C\}$ and $\rho(c) = \{s \mid subclass(s, c), s, c \in C\}$ are used to denote the set of its subclass and superclass concepts.

D. Deep learning techniques

Restricted Bolzmann Machines (RBM) are generative stochastic neural networks proposed by Hinton and Sejnowsk [21]. RBM have demonstrated exceptional performances for tasks with both labeled and unlabeled data [24]. A deep restricted Boltzmann machine (DRBM) is a deep neural network model with a stacking of many restricted Boltzmann machines (RBM) layers (Fig. 6) We used a deep learning mechanism [24] to mine deep semantic features automatically and analyze the role that these features play in defect type recognition. Using a feature analysis method, we abstracted four feature layers of classes in a database of porcelain ware and then vectorized every attribute of the database to a feature vector set. Finally, we analyzed the feature vector sets using an Ontology Based Deep Restricted Bolzmann Machine (OB-DRBM) to obtain recognition results.

Typically, a RBM contains a layer of visible units *v* and a layer of hidden units *u*, which are connected as a bipartite graph [25].

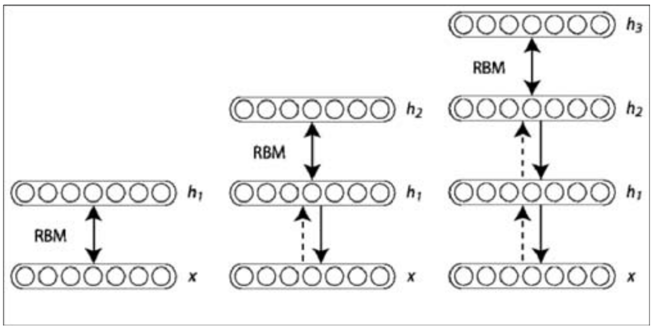

Fig. 6 Layers in a Deep Restricted Bolzmann Machine

The architecture design of the proposed OB-DRBM model is based on the methodology and algorithm presented in [26]. Given an ontology O, we composed the OB-DRBM model. Fig. 7 presents a sample OB-DRBM model following the Defect type ontology presented in Fig. 5. The architecture design follows a top down process from higher level concepts to lower level concepts.

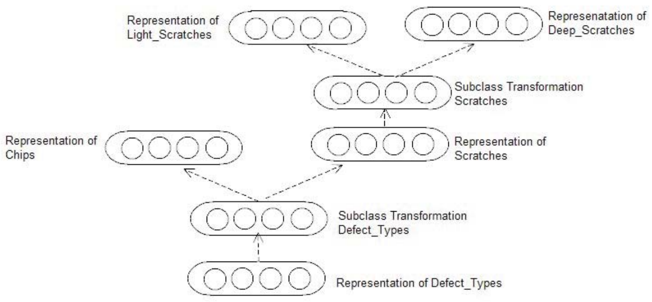

Fig. 7 OB-DRBM model for Defect Type Ontology

For example, the semantic softmax layer *SScratches* contains three output units, for *Light_Scratches*, *Deep_Scratches*, *OutofDomain* respectively. For data instance *{x, Deep_Scratches}*, the target output for *SScratches* is (0, 1, 0). At the training phase, through semantic reasoner query R (O, $x \rightarrow y$), we converted each labeled data $l = \{x, y\}$ to a set of promoted data instances, $l(k) = \{x, \pi(k)(y)\}$, for each semantic softmax layer. For each concept c and its corresponding DRBM module Dc, we also attached a multiple hidden multiple visible restricted Boltzmann machine (MHMV-RBM) layer Mc for subclass relation modeling [24].

The MVMH-RBM layer is a RBM variation designed to model the subclass transformation from a superclass to its subclasses [25]. In the OB-DRBM model, each DRBM module Dc for concept c is attached to its own semantic softmax layer Sc. The representation learned in Dc encodes the high level feature abstractions for concept c. Before feeding such a representation to subclass modules $D\,\rho(c)$, the MVMH-RBM layer learns a generative representation for both the input of subclasses features and representation in Dc. The subclass representation and raw input are further feed into subclass modules $D\,\rho(c)$ as input.

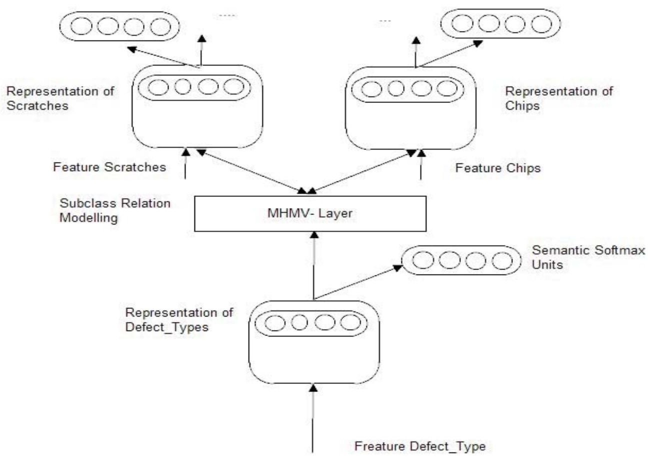

Fig. 8 An OB-DRBM architecture from Defect Type ontology

IV. Experiments and results

We used a porcelain ware corpus of more than 10.000 products for experimental data and extracted semantic information required for defect type recognition according to the feature representations described in the section before. Then, training and test samples were generated. We trained th the samples using OB-DRBM to generate a stable deep classifier, which could recognize the defect types in test samples.

The values of deep-classifier-related parameters number of epochs, batch size, momentum, and alpha were set to 1, 100, 0, and 1, respectively.

We trained the OB-DRBM model using a similar way as the conventional DRBM model [23]. An OB-DRBM model was first trained with greedy module wised and layer wised contrastive divergence (CD) as in [24]. Then we used stochastic gradient descent across all semantic softmax output to further fine-tune our model with labeled data. At the validation phase, the output of our OB-DRBM model contained a set of consistent outputs from all semantic softmax layer units. For example, y = *{Deep_Scratches, Scratches, Defect_Type}* is a consistent output for input data, *{x, Deep_Scratches}* (Fig. 7). We enforced this consistency using a logistic regression across all semantic softmax output configurations with consistency validation from a semantic reasoner as presented in [26].

Our primary goal was to explore the effect of formal semantics model with conventional DRBM model under the same context, including data distribution, meta parameters, training time and algorithms. In all experiments, we divided the dataset into 70% training, 15% validation, and 15% testing. The number of iterations over the training set was determined using early stopping according to the validation set classification error with an additional 100 iterations following the methodology described in [26].

We evaluated our model on the porcelain ware corpus. The description of the entire experiment is not the subject of this paper. Table I gives the classification performances for two types of defects, namely chips and scratches. Our OB-DRBM model outperformed the conventional DRBM models. We tested the recognition performance of OB-DRBM in comparison with DRBM. Introducing feature layers to OBDBM can help improve recognition performance. In fact, test results have shown that adding feature layers can improve system performance regardless of the number of RBM layers.

Table I. Classification performance on porcelain ware industry

Defect_Type	Accuracy OB-DRBM	Accuracy DRBM
Chips	87,5%	72,02%
Scratches	78,9%	62,75%

Other type of experiments we have conducted were automated defect inspections on images. Automated inspections have been designed by using the software from National Instruments, namely Visual Builder for Automate Inspection (VBAI) [27]. An example the entire process of inspection is captured in Fig. 9.

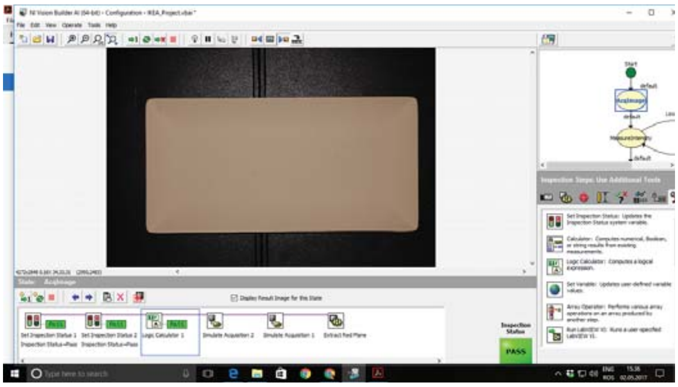

Fig. 9 Automated defect inspection in VBAI

This type of experiments have been carried out in the framework of the image acquisition/interpretation module in the architecture presented in Fig. 2.

V. CONCLUSIONS AND FUTURE WORK

In this paper we have presented a CPS architecture designed for intelligent management of defects that is applicable in the porcelain industry. Various sensors acquired image data, while the information has been processed by using automated computer vision techniques, knowledge management and machine learning. The processed information was further integrated into a decision making system and transmitted to actuators/robots. The experiments and results presented in this paper are only preliminary achievements. More experiments and validation will be achieved in the next phases of the project. In the future, the performance and scalability of OB-DRBM model will be extended to image analyses that have been acquired in the first block of the CPS architecture.

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