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R. Schmitt / A. Pavim

Flexible Inspection of Small Series Production Systems through the Use of Dynamic Sensor Fusion Principles

ABSTRACT

The world market competition currently boosts the innovation and customisation of various products. The increased product variety being offered and the flexibility of small series production complicate the automation and control of the manufacturing tasks, resulting in great challenges for the quality management systems. In the case of mass production, the inspection systems that assure the quality of the products/processes can be planned in advance, according to the fixed measurement requisites in which they are located. The inspection solution is then configured in a rigid automatic sensor/actuator chain. This rigid configuration is actually insufficient and error-prone for small series production, because the measuring strategy is totally dependent on the "fixed" features of the objects under inspection and the automated inspection chain has little knowledge about what is actually being performed. Flexible industrial metrology with a higher cognitive inspection level plays an indispensable role, in order to maintain the quality of products and processes and simultaneously attend the flexibility of the small series and individualised production. By flexible small production lines, the inspection system must be able to deal with many different product variants, greater amount of features must be extracted and also intelligent decisions (cognition) are required.

This work presents a short introduction about the challenges faced by the inspection of small series production, which evidences the need for novel inspection strategies. In the sequence, based on the already existent sensor fusion principles, the Measurement on Demand (MEOND) concept is presented as a possible solution to build intelligent and dynamic inspection systems for the small series production. Aspects about cognition and self-optimisation are discussed in accordance to the MEOND concept. Possible application scenarios for this concept are discussed among the flexible inspection of automobile headlights and the self-optimised assembly of a solid state laser.

Keywords: small series production, flexible metrology, sensor fusion, cognition, self-optimisation, MEOND.

INTRODUCTION

The market competition originated from countries with low-cost work forces puts pressure on enterprises world wide and leads to a focus on innovation and product customisation. This fact is compelling industries to improve the efficiency of production processes, e.g. by increasing the automation level or improving management strategies for quality, innovation and information, so that an optimised value-added chain can be achieved while keeping the production costs reduced.

Taking a look at industrial production today, two dilemmas that are closely related affect the efficiency of production systems [1]. The first dilemma is related to the “scale versus scope” problem. Either the production system is designed for a high scale output without variances in the product design (critical masses, mastered processes, high synchronisation and output), or it is designed for highly individual products down to a single item production (one-piece-flow, dynamic processes, limited synchronisation and output). The second dilemma is related to the “value-oriented versus planning-oriented” production. The value-orientation approach focuses on the value-adding process (less planning, preparation, handling, transport), while the planning-orientation approach focuses on extensive planning to optimise value-adding (modelling, simulation, information gathering).

In order to reduce the first dilemma of scale versus scope, production systems must be provided with more flexibility (flexible automation, greater number of sensors/actuators, more information acquisition/storage/flow). Every automated system that restricts the work with a greater product variant or limits the capabilities of the production processes are directly constraining the customisation/individualisation of the production. Flexible automated systems require therefore the capability to adapt themselves to their surrounding conditions [2,3]. But while this added flexibility and adaption capabilities help reducing the first dilemma, at the same time it creates a greater gap between the planning- and value-oriented approaches. A greater amount of planning and organising tasks arise due to the increased complexity introduced when providing such flexible capabilities to the production processes. One idea of the “Aachen House of Integrative Production*” is to use cognition and self-optimisation strategies as key factors to reduce the increased dilemma between planning- and value-orientation and enable a flexible and adaptive automation of the production without needing to strongly invest on planning tasks (Figure 1).

* http://www.production-research.de/

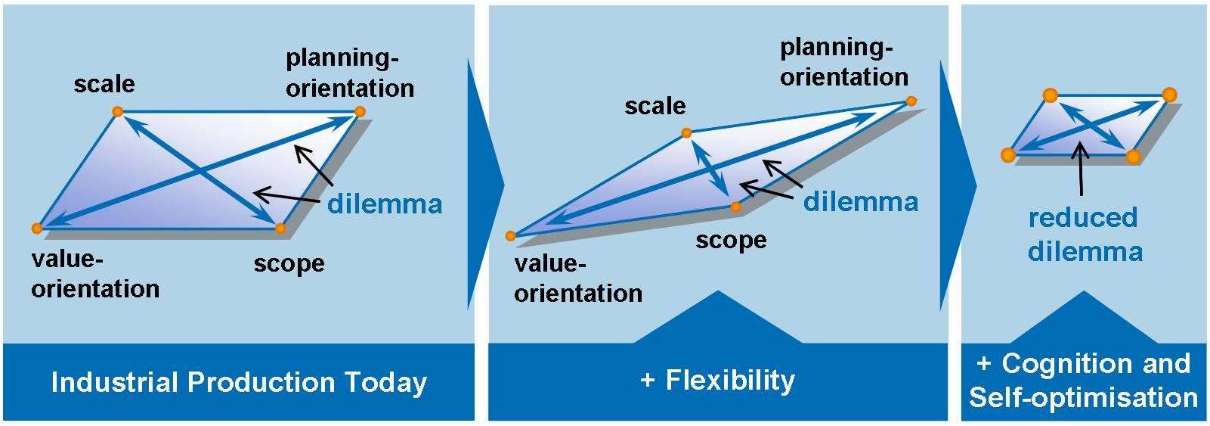

Figure 1: Concepts for enabling tomorrow's production strategies in high wage countries.

FLEXIBLE METROLOGY AND SENSOR FUSION

The increased product variety being offered and the flexibility of small series production (scope) complicate the automation and control of the manufacturing tasks, resulting in great challenges for the quality management systems. In the case of mass production (scale), where the product variety is low, the inspection systems that assure the quality of the products/processes can be planned in advance, according to their fixed measurement requisites and the environmental conditions in which they are located. The inspection solution is then configured in a rigid automatic sensor/actuator chain, which accomplishes exactly the desired inspection tasks. This rigid configuration is actually insufficient and error-prone for small series production, because the measuring strategy is totally dependent on the "fixed" features of the objects under inspection and the automated inspection chain has little knowledge (lack of cognition) about what is actually being performed [2,4]. Flexible industrial metrology with a higher cognitive inspection level plays an indispensable role, in order to maintain the quality of products and processes and simultaneously attend the flexibility of the small series and individualised production [3].

By flexible small production lines, the inspection system must be able to deal with many different product variants, greater amount of features must be extracted and also intelligent decisions (cognition) are required. These decisions are important not only for adapting the inspection system to the currently product/process under test, but also for reaching reasonable and more robust evaluation criteria from the product/process quality level and the best way to optimise it [2]. Distinct measurement principles or configurations will be often needed for the inspection of objects with different shapes, properties and/or materials [4]. A multi-sensorial approach is thus needed to improve the inspection range and flexibility of a small series production line, so that the distinct features of different industrial parts can be inspected in an intelligent way, independently of their surface or even internal properties. Optical metrology and non-destructive testing (NDT) inspection methods provide a very good basis for implementing intelligent and dynamic multi-sensor systems for the inspection of macro- and micro-systems, because of the benefits of such measuring principles (fast and accurate measurement results, touchless, non-invasive) [4,5,6].

A flexible metrology strategy is currently under development, which is called Measurement on Demand (MEOND) [6]. The basic idea of MEOND is the creation of a modular sensor pool (or universal measuring configuration), responsible for handling the inspection tasks of a small series production facility. That means planning and arranging the correct sensors within the production line. The intelligence required for controlling the whole sensing system must also be foreseen, taking into consideration the product variety and information flow control, as well as the algorithms needed for taking cognitive decisions. The goal is to provide the minimal sensing configuration able to dynamically handle all the required inspection tasks correctly (or “on demand”), by understanding what is being inspected under the current variable conditions.

An inspection system that fulfils these requisites will usually be based on dynamic sensor integration and fusion principles [7,8] and supported by cognitive capabilities (features localisation and recognition, classification, decision taking), which may usually be found among artificial intelligence methods [9,10,11], such as those based on probability principles, neural networks, genetic algorithms and fuzzy logic.

Sensor integration means the synergetic application of multiple sensors for solving a detection, classification or identification problem. Sensor fusion corresponds to the combination of the sensors’ data for obtaining new or more precise knowledge on the involved features, events or situations. Dynamic sensor integration and fusion means that the control intelligence must decide, for each new inspection situation (change of environmental conditions, change of product or process features), which are the best sensor combinations and how their acquired data can be fused to achieve more robust decisions about the production process (Figure 2). The choice of the sensors and their configuration is based on the kind of measurement to be performed among the process/product (geometry, layer thickness, surface roughness, topography, temperature, internal features etc.) and on the environmental conditions (temperature, pressure, illumination, vibration etc.). A global knowledge database is useful for such purposes, as it assists the higher decision levels of the system to configure the different

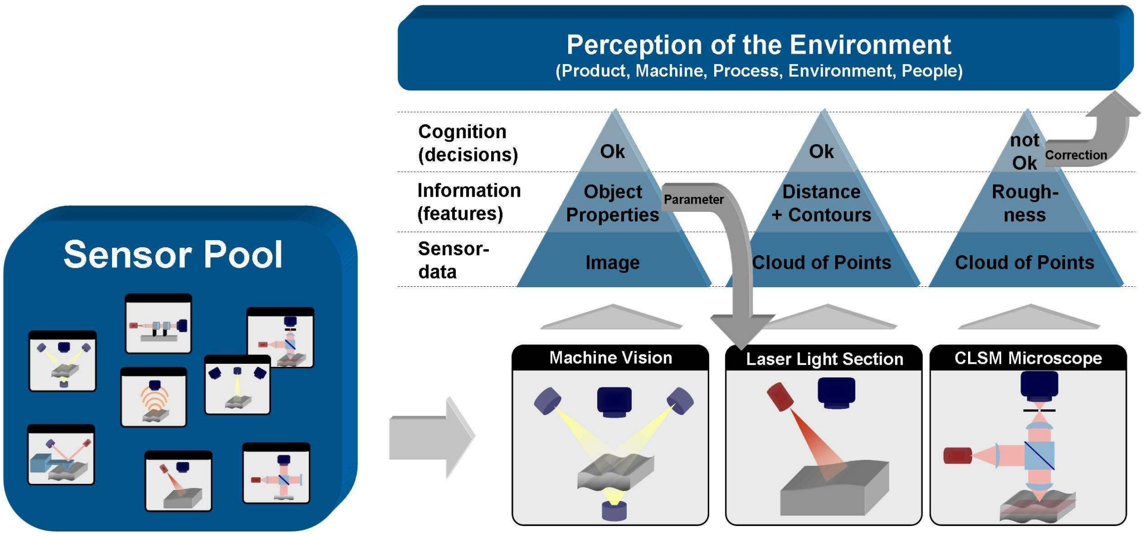

Figure 2. Illustration of the MEOND principle, depicting the sensor pool (left) and the dynamic decisions (right) taken by the control system.

sensors, based on its successful previous experiences.

The fused information can be raw data provided by the multiple sensors as well as a mathematical interpretation of these data (object/environment properties). It is expected that this combination of data can increase the system capabilities and performance (especially reliability and robustness), which must be superior to the results achieved with the individual sensors alone.

The process of obtaining conclusions about the measuring results of a multi-sensor system usually combines redundant or complementary information [7]. The instability of the sensors' signals can be diminished through redundancy, as well as the signal-to-noise ratio and measurement robustness can be improved. Complementary information may also be obtained from heterogeneous sensors and then combined for taking important decisions about the system, which could not previously be analysed with the application of individual sensors. These both integration concepts help eliminating ambiguity in the interpretation of individual information sources.

The fusion of data can also be classified according the abstraction level of the used data among three main groups [7,8]: signal (sensor data) level, features (information) level and symbols (cognition) level. In the signal level the raw data provided by the individual sensors are directly combined. As a pre-condition, the signals must be compared, registered and synchronised. In the features level only the extracted features or descriptors of the signals are combined. This is usually the case for signals that can not be directly combined. In the symbols level, only high-level interpretations of the signals (for example, classification results) are combined together to achieve final decisions usually based on probability levels. Both in the features and symbols level, great part of the information of the individual signals are lost.

Sensor integration and data fusion are thus the key factors for conceiving flexible automation systems, which can be applied within production environments and enable the dynamical inspection of small series production. But the fusion of sensors may even complicate the production tasks if no cognitive methods for interpreting the greater sensing capabilities of the system are provided. The following section discusses briefly about cognition aspects and how it may support the creation of self-optimised systems.

COGNITION AND SELF-OPTIMISATION ASPECTS

The trends for miniaturisation and individualisation of the production require a great effort in designing flexible technical systems, which must be able to work with and add value to products as efficiently as the current mass production systems already do, but dealing with variable productive conditions. Cognitive capabilities such as perception, reasoning, learning and planning turn technical systems into systems that know what they are doing [12]. To better comprehend these key cognitive concepts, it is useful to analyse such technical systems inside a so called cognitive-based perception-action closed loop, which is depicted in Figure 3. It illustrates the architecture of a cognitive system with multi-sensor perception, cognition (learning, knowledge, action planning), and action. These key concepts can be understood as follows [12]:

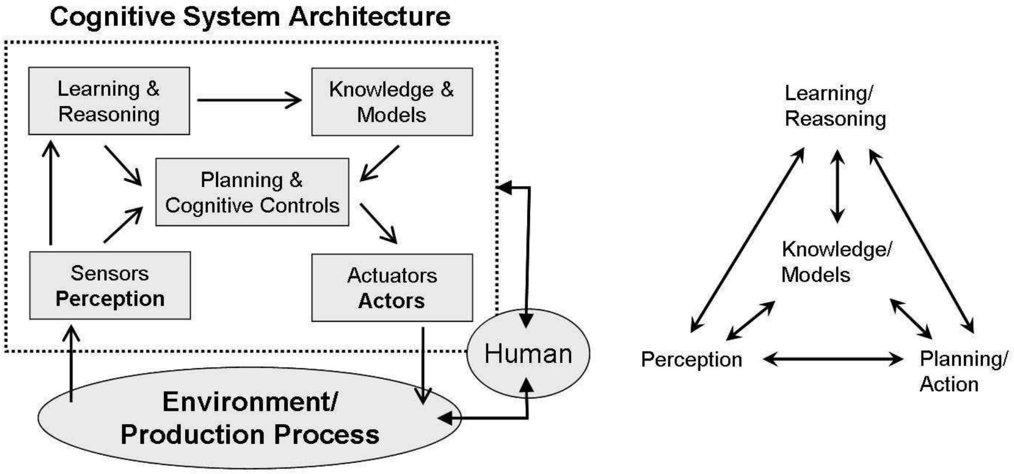

Figure 3. The cognitive system architecture: The perception-action closed loop (left) and the inter-relationship of the cognitive capabilities (right). Source [12].

- **Perception** is the acquisition of information about the environment and the current object under study. Part of this information is processed and new relevant features and information can be generated through e.g. recognising, classifying and locating objects, observing relevant events/situations and retrieving context information about it.

- **Action** is the process of generating behaviour to change the surrounding environment and complete the tasks that were designated to the system, according to the decisions that were taken about the environment perception.
- **Knowledge** can be seen as consisting both of a declarative and a procedural instance. Declarative knowledge means recognising and understanding the real information known about objects, ideas and events in the environment and their inter-relationships. Procedural knowledge handles actually the information regarding how to execute a sequence of operations.
- **Learning** is the process of acquiring information and reorganising such information in order to derive new knowledge. The learned knowledge can relate to skills, experience, or being taught. Learning causes a change of behaviour that is persistent, measurable and specified. It is a process that depends on experience and leads to long-term changes in behaviour.
- **Reasoning** is a cognitive process by which an individual or system may infer a conclusion from an assortment of evidence, or from statement of principles.
- **Planning** is a process of generating representations of future behaviour, prior to the use of such plans, to constrain or control current behaviour. It comprises reasoning about the future in order to generate, revise or optimise the intended course of action.

These key concepts are studied by some interdisciplinary but close related research fields, as e.g. natural cognitive sciences, control theory and artificial intelligence. Through the use of some tools and principles from control theory (feedback, robust and adaptive control rules, modelling through differential equations and automata etc.) and artificial intelligence (probabilistic estimations, decision trees, support vector machines, neural networks, reinforcement learning etc.), cognition aspects can already be provided within technical systems. But in order to achieve a real autonomous and intelligent automation level for the production, cognition must be applied and connected along all the production layers, from the low technical levels to the high planning levels.

Through the use of higher cognitive connection within the production environment it is even possible to conceive self-optimised systems [13,14]. These are intelligent systems that present the capability to react autonomously and flexibly against their surrounding environmental conditions, the interference of the external users/systems, or also their own dynamical behaviour, modifying their goals and adapting their parameters/structure in response to these dynamic factors. These systems are usually able to learn with their own experiences and remember from past events, which may help predicting new events and optimising their behaviour in future situations [13].

By definition, self-optimisation is characterised by the simultaneous and dynamic interaction of three factors [13,14]:

1) Analysis of the current system situation;
2) Determination of the system objectives;
3) Adaptation of the system behaviour to the new surrounding conditions.

The first factor means perceiving the system actual state and all the significant modifications in its surrounding environment, which may be caused by different interference sources. The second factor allows the system to define autonomously its next goals by selecting the most adequate among a pre-defined list, adapting the current existent goals to the current situation, or even generating new ones. The third factor is achieved by changing the system's parameters, structure and behaviour, in order to follow the new set of defined goals and close the control loop. The optimisation concept is usually introduced among the second or third factors.

The optimisation methods can be divided into three classes [13]: model-based, behaviour-based and hybrid optimisation. The model-based optimisation method occurs by linking the interpretation of the system and environment status with their mathematical description (model), allowing their algorithmic comparison, in order to adapt its goals and perform optimisation. The behaviour-based optimisation method uses a knowledge basis and the system past experiences together with cognitive techniques to choose an adequate behaviour for the system among some pre-defined behaviour forms. The hybrid optimisation occurs when both methods are combined.

In the sequence, two different application scenarios for the use of the MEOND technology and their respective cognitive and self-optimisation aspects are commented in more details.

APPLICATION SCENARIOS FOR THE MEOND TECHNOLOGY

Applying MEOND to the macro-/micro-system world consists in defining an adequate modular set of macro-/micro-metrology techniques (sensor pool), and implementing the control intelligence that will guide them during each new measurement request coming from the small series production line. Two examples will be next provided: a possible scenario for the flexible inspection of automobile headlights and the self-optimised assembly of a solid state laser.

Flexible Inspection of Automobile Headlights

The automotive industry features many distinct examples of mass and small series production of automobile components simultaneously. New automobiles are constantly being conceived with novel technologies and design details that must attend at the same time a different number of market niches and maintain high quality and customer satisfaction levels. Some companies prefer to concentrate their efforts to introduce advances and optimise the production value-added chain by simply improving the current existent manufacturing processes and keeping a low product variety. Other companies intend to offer the clients a greater diversity of product models and therefore concentrate more efforts on planning the different details and the production flexibility needed to attend the requirements that arise with smaller production batches.

The inspection of high quality automobile headlight glasses demands flexible and specialised sensing techniques, in order to perform a 100% quality inspection from a great diversity of product models. The current automobile headlight glasses feature a great diversity of design details (lines, curvatures, markings) with distinct geometries and possibly also magnification transfer functions, for focusing the spot lights in a precise specified distance. Not only these design and geometric details must be inspected to match the product specifications, but also the presence of possible manufacturing failures, such as material defects, scratches, cracks and dirt.

The automatic inspection of automobile headlights through specialised optical sensing systems is already performed in industrial environments by the use of modular and enclosed machine vision stations, in which the headlight glasses mounted on adequate pallets are fed and displaced within an automated inspection system through conveyor belt systems (Figure 4).

Figure 4. Automated system for the inspection of automobile headlight glasses (left). Headlight glasses mounted on pallets fed by conveyor belts (middle). Internal modular machine vision stations (right).

The basic automated inspection system consists of two machine vision stations using line-cameras and especial backlight and darkfield illumination strategies to enhance exactly the needed features of the headlight glasses. By a normal operation of the system, the different features of the headlight glasses are extracted correctly from two different images delivered by each machine vision station respectively. Even the presence of small dirty points can be detected by the system.

Although the synchronisation of the system and the image quality from the machine vision stations allow a perfect analysis and inspection of all the relevant features of the headlight glass, a considerable quantity of pseudo-rejections is still delivered. The reasons for that are the extreme rigid configuration of the machine vision stations and the lack of intelligence of the automated system to correctly identify the localisation, geometry and displacement of the relevant headlight features. To avoid considering a specific design detail of the headlight glass as a possible scratch or crack, the inspection for failures is restricted to rigid regions of interest (ROI) in the acquired image (Figure 5). A small false displacement from the headlight pallets, causing the headlights to be falsely positioned in front of the cameras, is enough to disturb the correct inspection of the product features. With such an inspection strategy it is also impossible to set different kinds of headlight models to be inspected simultaneously, as no recognition of the product and from its features is performed during the operation of the automated inspection system.

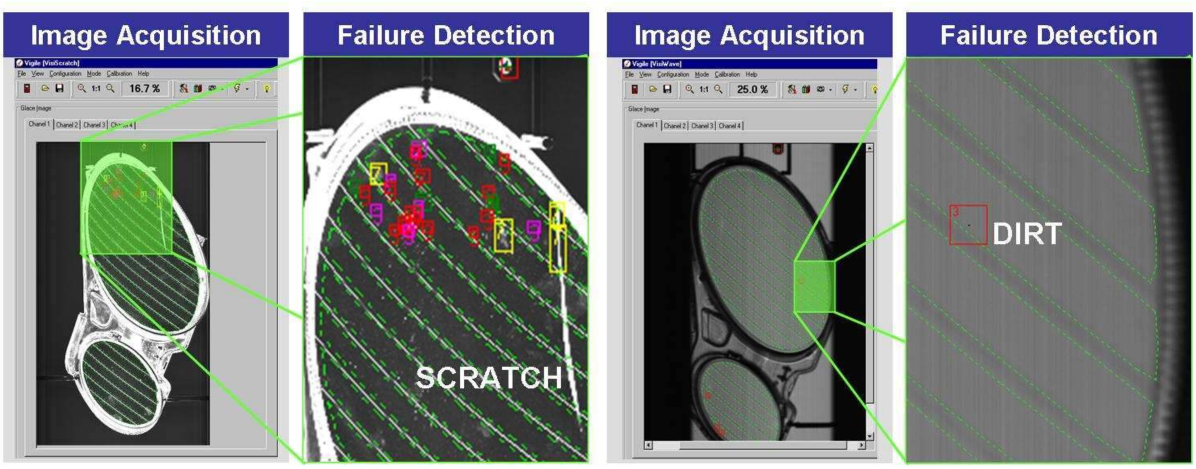

Figure 5. Measurement results from the machine vision stations with darkfield (left) and backlight (right) illumination strategies. ROIs are used to avoid inspecting design details as failures.

In the scope of the "Brazilian – German Collaborative Research Initiative on Manufacturing Technology" – BRAGECRIM, this automated inspection system is being implemented in the Laboratory of Machine Tools and Production Engineering WZL at the RWTH Aachen. A new inspection approach with enhanced sensing capabilities, higher flexibility and cognitive level is needed to avoid the pseudo-rejection errors and to allow the simultaneous inspection of different product variants. Following the MEOND principle a sensor pool consisting on the following measuring techniques was planned (Figure 6): a new machine vision station with megapixel camera, zoom lenses and flexible illumination strategy, responsible for identifying the product model and also its main features; a thermographic station with a megapixel camera, for identifying some special features of the product (especially contours); and a 3D measuring system (e.g. fringe projection or stereoscopy) for obtaining the height profile and generating a complete 3D model of the product. The previous existent machine vision stations are also kept in order to perform the fine inspection of the product features.

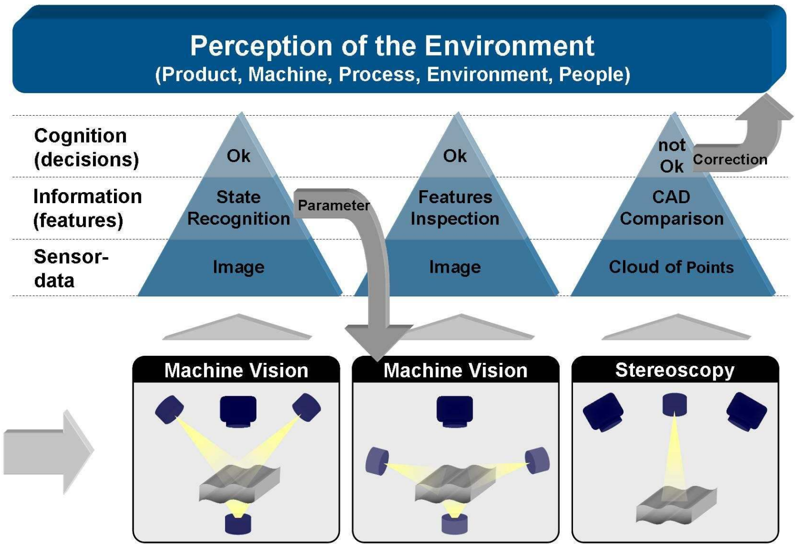

Figure 6. Illustration of the MEOND principle applied to the flexible inspection of automobile headlights.

The first part of the project concentrates on the implementation of the new flexible machine vision station and the cooperative integration and fusion of its data with the other two already existent machine vision stations. By loading new headlight glasses into the machine, the current state of the whole inspection system is monitored, so that the inspection goals can be dynamically defined. The type of the headlight is firstly recognised by the new machine vision station, as well as its localisation and orientation, through the use of image processing and artificial intelligence techniques. With this prior information about the product, the next machine vision stations may be correctly configured to perform the fine inspection of the product features taking into consideration the type of the headlight (car model), its side (left or right headlight), and its correct displacement within the pallet. Together, the combined sensor data are used for delivering a global decision about the quality level of the product and avoid generating pseudo-rejections. The need for human assistance is yet discarded for configuring the system when a different headlight model is loaded into it, as the system already knows what it is inspecting. Due to the characteristics of the headlight glasses, which absorb great part of infrared radiation that is emitted in their direction, a thermographic camera could be successfully applied for inspecting the headlight contours and some design details, which can be extremely difficult to segment with traditional illumination strategies. This thermographic measuring station is currently under study and is planned to be integrated to the system during the next project phases, as well as the 3D measuring station, for the profiling and 3D-model generation of the product.

Self-optimised Assembly of a Solid State Laser

The assembly of manufactured components and testing functionality of products are generally the last activities performed in a production line, which are usually expensive tasks. In some cases, like the assembly of optical components (achromates, microscope objectives and lasers), the assembly process makes up to 80% of the total cost of the product, what leads to a great demand for automating their assembly process. The quality of optical devices directly depends on the manufacturing quality of their components and on their precise assembly, which is still manually performed. The assembly automation of a micro-laser device is currently being worked within the scope of a major project – the "Aachen House of Integrative Production". The goal is the self-optimised and automated assembly of a micro-laser [15,16], which is developed by the Fraunhofer ILT. It consists on a diode-pumped solid-state (DPSS) laser arranged with a planar configuration that facilitates the automated assembly (Figure 7). All its optical components can be positioned and assembled from above. They are mounted (soldered or bonded) on a coated ceramic carrier plate without the possibility of readjustment after the assembly process.

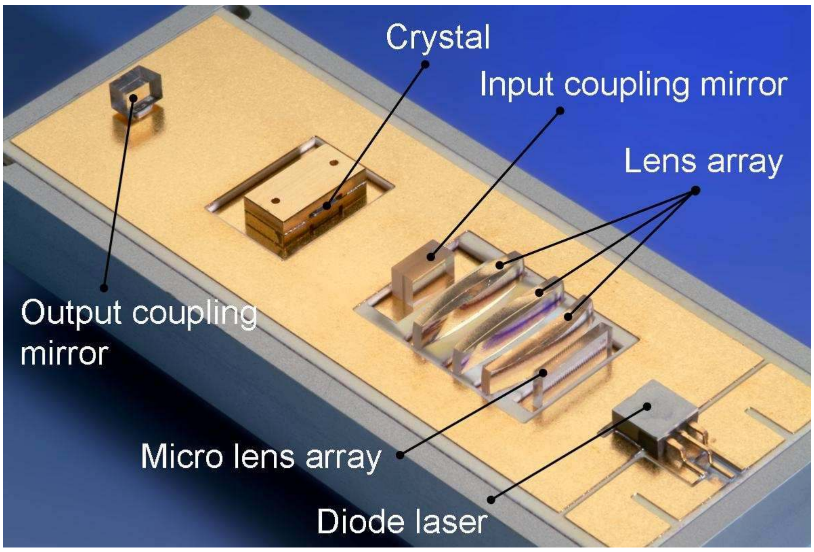

Figure 7. Demonstrator of the laser device designed for the automated assembly. Source: ILT.

The older model of the micro-laser was assembled completely manually in a non-systematic and empiric way, demanding thus, very high expertise for positioning the components and attending the minimal quality specifications. The automation approach is based on a flexible assembly module, which makes use of robots for the positioning and assembly of the laser components. The whole system must be continuously updated with information (from multiple sensors) about the assembly process, so that it may learn from its past experiences and improve itself constantly.

Following the MEOND principle a sensor pool consisting on the following measuring techniques was planned (Figure 8): a CCD-camera-based laser beam inspection system for monitoring the laser quality; machine vision for monitoring the fine positioning of the optical components; thermography for monitoring the components joining process (soldering/bonding); and a laser light section sensor for obtaining the height profile of the assembled components and generating a complete 3D model of the assembled micro-laser (allowing CAD comparison).

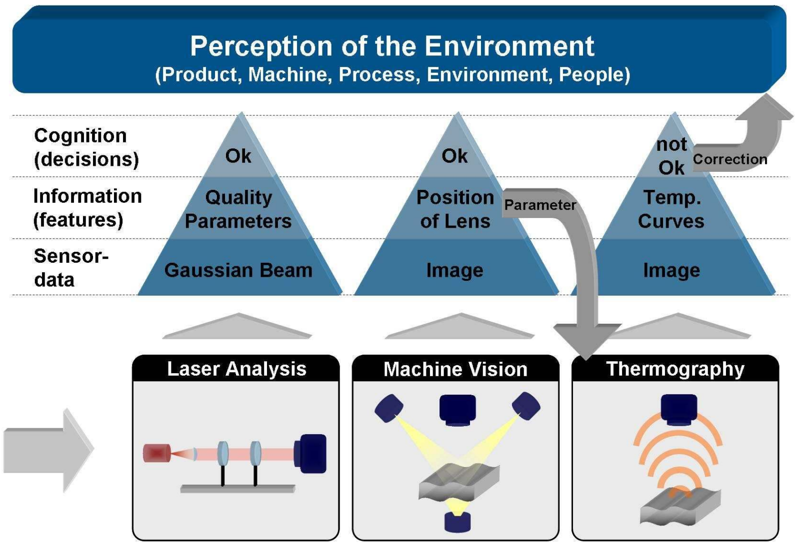

Figure 8. Illustration of the MEOND principle applied to the automated assembly of the DPSS laser.

The first part of the project concentrates in the cooperative sensor integration and fusion of the laser beam inspection system and the optical components positioning monitoring, which must assist the robots in the components manipulation process. A first lens is roughly positioned by a manipulation robot on the laser plate, in front of the laser diode. This rough initial position for the lens is obtained from a system model or from previous assembly experiences. The precise adjusting of the lens position is performed then by a micro-manipulator, which is coupled at the same robot. This adjusting process is guided through the analysis of the laser beam parameters, where an optimal beam behaviour is searched during the fine positioning of the lens. Next, the machine vision system monitors and determines through image processing techniques the accurate absolute position of the lens, because the manipulation robot can only retrieve relative positions. Together, the combined sensor data reflect the current complete state of the system and enable it to learn the fastest way to find the ideal laser beam and to optimise itself in the next assembly iterations (Figure 9). The introduction of new lenses in the assembly process increases the complexity of finding an optimal configuration for the whole set, because after a lens has already been correctly positioned, the insertion of a new component disturbs the behaviour of the laser beam, depending on the algorithm being used for the systematic assembly. In this case, the measurement and manipulation tasks should also be assisted by a mathematical model and simulation, which can estimate best initial points for the positioning of each optical component. Based on the model and on the simulation results, the system can find and converge quicker to the optimal configuration of the whole set.

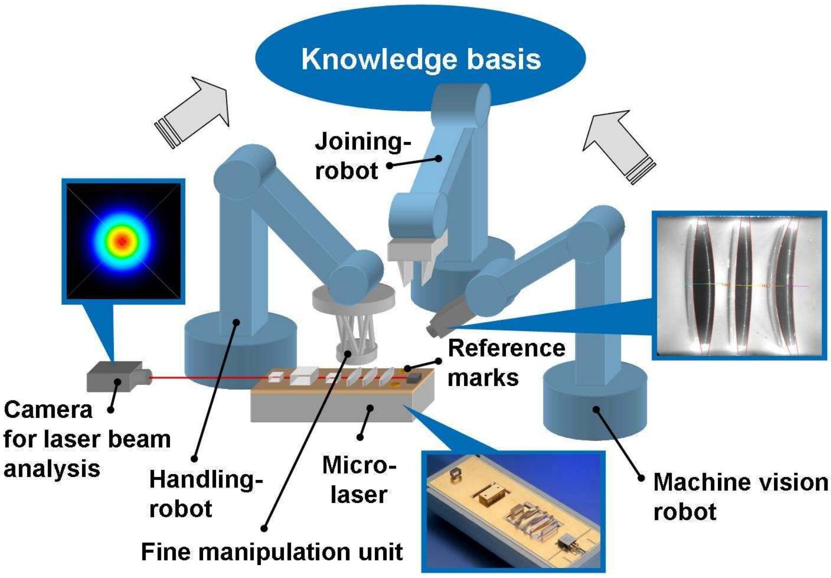

Figure 9. Combining different measurement information to enable learning and optimisation.

When the fine positioning of the lenses has achieved its optimum, they must be definitively joined to the laser board. The process involves heating of solder or glue elements under the optical components. To guarantee that the components will remain fixed enough after the joining process, the temperature curves underneath the optical components have to be monitored, so that a better distribution of the joining material is achieved between the laser board and the components' bottom surface. This process is currently under study with thermographic cameras. The other foreseen measuring task (laser light section) is planned to be integrated to the system in the next project phases.

CONCLUSIONS

The current requirements for a cost-effective industrial production in high wage countries demand a higher degree on innovation towards the conception of intelligent production systems, which must be able to deal with an increased product variety and handle with the flexibility of small series production. Automated systems that restrict working with a greater product variant or limit the capabilities of the production processes directly constrain the customisation/individualisation of the production. Flexible automated systems require therefore the capability to adapt themselves to their surrounding conditions, which means that they must be supported by novel and intelligent sensing strategies, able to enhance the perception capabilities of the production system.

All these requirements complicate considerably the automation and control of the manufacturing tasks, offering great challenges for the quality management systems. Cognition and self-optimisation strategies are seen as key factors to conceive more flexible systems, reducing the increased dilemma between planning- and value-orientation and enabling an adaptive automation of the production without needing to invest strongly on planning tasks.

Flexible industrial metrology with a higher cognitive inspection level plays an indispensable role, in order to maintain the quality of products and processes and simultaneously attend the flexibility of the small series and individualised production. No single measuring technique has been found until today, which is able to perform multiple inspections of many different features of a manufactured object. It is clear that each measuring technique is better suited for inspecting specific kinds of features or can be better adapted to certain kinds of applications and that is why sensor fusion principles have become ultimately a great trend for the metrological field. New metrological systems providing such sensor fusion features go already towards this trend direction, focusing the creation of universal measuring systems. Anyway, they neither provide an easy way to correlate the measuring data acquired with the different sensors, nor provide an intelligent way to choose the correct sensors for the desired measuring tasks. The MEOND principle was then introduced as a possible solution to build intelligent and dynamic inspection systems for the small series production, following flexible and dynamic sensor fusion principles. Possible application scenarios for this concept were discussed among the flexible inspection of automobile headlights and the self-optimised assembly of a solid state laser.

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