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Vision based, statistical learning system for fault recognition in industrial assembly environment

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***Abstract* – The paper presents a statistical learning system based visual solution developed and applied for fault detection in industrial environment. As a mobile vision system the area of use was the automatic detection of rare faults in complex assembled objects. The object detection, the fore- and background separation, and the multi-model database enables the system to manage irregular batches of the different objects. A multi-model database guarantees that the object is compared with the statistically most relevant model, therefore it reduces the number of false alarms. The developed system is able to detect faults with the size of 2% of the total picture based on previously learned models.**

***Index Terms* – Computer vision, image analysis, learning system, model-based vision, pattern recognition, vision for industrial assemblies.**

I. INTRODUCTION

Product quality is always a primary concern in industry. In mass production the manufacturers must protect the customers from receiving a defective product. Before starting a new technology or product a risk evaluation should highlight the possible defects.

On the assembly lines most of possible defects are visually noticeable: swapping parts, not properly positioned parts or possible damages. These failures indicate a high amount of visual system on production lines, each taught for dedicated “known” failure mode.

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The processing algorithm is a pixel to pixel comparison: reading numbers or codes, detect edges, etc. However, sometimes new failure modes came up, which were judged as impossible or simply nobody thought they could happen. These failures can be grouped into one category: the “unknown, rare problems”. They happened only once, but caused customer complaints. At the moment, there is no error detection system which can find these unique failures. This was the background where the idea of a learning vision system came from. The imagined system is not created to find exact failures, it should only review the products and check if they are all the same. The system has no connection to the assembly process, it only carries an external visual observation and indicates if products are not the same. In order to prepare a general vision based production supervision solution, the system should be mobile for easy relocation, and must work without any additional light source, only by using the illuminance of the environment. There is only visual connection to the line via the camera, also supporting the easy relocation. It should automatically detect the presence of the product and should deal with bothering movements in the background, too. With these conditions, all negative limitations of the commonly used vision systems could be eliminated.

The system should work as if someone would be standing next to the assembly line and watching the products. This person doesn’t have to know the details about the way how the product works, just check the visual appearance and know that all of them should look the same. After the system is placed next to the production line only the camera needs to be adjusted in some basic visual observation parameters and the learning phase can begin. During this phase the user has to ensure that the first five or ten parts are good. When it’s done, the system will also know that all the following parts should look the same. If one looks different it just indicates it and someone who knows the product will check if it is an error or an allowable difference.

Due to many customers with different demands, high component level proliferation is given. One of the most complicated function will be the handling of the different product types. In case it’s only a small difference between two parts, it can be a failure, if the deviation is bigger or it can be a new type, however, sometimes a small difference can also mean a new type.

II. STATE-OF-ART: ALGORITHMS AND INDUSTRIAL VISION

The given fault detection task has a number of specific features which are not typical for traditional industrial inspection. With a reasonably low false alarm rate, the system has to signal very rarely occurring, unspecified assembly defects in unknown positions. This lack of fault model means that learning the potential faults is quite difficult since they appear just as “significant deviations” from the “normal” fault-free state that can be called “anomalies”. As discussed in [1], such situation arises in inspection of modern high-integrity systems where standard classification techniques are not applicable. In addition, the solution has to cope with frequent visible but allowable deviations, which necessitate careful checking all major deviations.

Similar phenomena are studied in various sciences as well as in telecommunication, banking, business and security tasks, under different names: defect, anomaly, motion, change, novelty, unusual behaviour, unexpected event, abnormality. Despite the obvious similarity, however, finding a common mathematical background is not easy because different areas use different mathematical tools and perceive the problem in different ways [1,2,3,4]. Fortunately, there is a general understanding that the root of the problem is in detecting the so-called outliers [3,4] that differ from a regular behaviour represented by some statistical model.

The principles of novelty detection and processing are discussed in [1]. A novelty is a phenomenon, event or data that does not fit the current model. When a novelty is detected, the system has to decide whether to accept it and update the model, or to discard it and add it to the set of negative examples or patterns. The criteria of a good novelty detection system include maximising the detection rate while minimising the false alarm rate. The appropriate normalisation of data, the small number of parameters to tune, the capability of generalisation without increasing the false alarm rate, the scalability, and the capability to work with small and noisy learning sets is required, too. Most of these criteria aim at the robustness of the system since the improperly handled outliers can spoil the model.

A critical related issue is that of rejecting a sample without decision making in case of uncertainty. Most of the defect recognition systems have a threshold parameter specifying the sensitivity of the system. The given application has to address this problem since the lack of decision may result in undetected faults. Here, an option is to delegate the decision to a human operator which is possible if such occasions are rare.

The survey [1] discusses a number of mathematical tools that can be used for novelty detection, including the parametric ones such as Gaussian Mixture Modelling (GMM) [5], Principle Component Analysis, Singular Value Decomposition (SVD) [6] and clustering; and the non-parametric ones such as k-nearest neighbours and Parzen windows. The paper [1] mentions also several industrial applications, e.g., inspection of aircraft engines using signal processing. Another relevant survey of industrial computer vision is provided in [7].

Change detection in images and videos [2] has numerous applications in different areas including industrial inspection. Despite its apparent simplicity, this problem is not easy at all as changes may appear due to many significant and insignificant factors such as object motion, shape variation, occlusion and discussion, illumination variation, shadows, camera motion or changing background. GMM [5] and SVD [6] are popular tools for background modelling [8,9] and change detection in case of static camera. These tools can be useful in the given industrial challenge, as well. However, special attention should be paid to irrelevant appearance changes of the inspected object because of noise, illumination changes, mapping distortions due to object motion, background variation and other practical issues.

In conclusion, the given fault detection task is a complex, challenging problem that needs careful planning, combination and application of sophisticated mathematical, programming and engineering tools.

There are a lot of visual recognition systems in the automotive industry for measuring, and analysing product components, for investigating the accuracy of the manufacturing process, checking the known part presence or absence, sorting products, or reading and verifying data mark. Some of them work with pixel-pixel comparison, with line-trigger, or use pre-trained reference pictures, or pre-set limits, but they do not work with complex parts, with irregular line sequence, or with model variance without user intervention or training.

Some paper deal with visual applications in industrial field, in connection with leaning-based and knowledge-based algorithms, but most of them investigate only position detection [10], or variety of the parts [11], but not complex assembly.

Woods el al. worked out a frame-based system for modelling a visual task, where the user has to program the system, but no vision specialist is required. This system implemented for several practical applications e.g. to chromosome classification, and brake assembly investigation for crack detection [13, 14], but it needs a user for operation, and cannot learn, and use previously acquired data.

As conclusion, no ready-made solution is available, which is able handle this complex vision task, so a novel solution was required to handle this supervision problem.

III. Hardware system and requirements

Parts of the hardware unit had to be selected carefully, to achieve real-time processing with approximately 30 second cycle time, while the algorithm has to solve many tasks: it has to detect the object from motion information, collect frame pictures from it, separate the object from the background, find the statistically most corresponding model with comparing the object to all stored models, and analyse the variance, using statistical methods, and finally, making the decision that the object is imperfect or not.

The system has to be mobile for the easy relocation, which means that it has to be independent from the assembly line, and exclude the usage of external light source, e.g. because it can disturb the operators.

The only information coming from the object is the motion, but it is not moving with constant speed, and not moving always (it can stop whenever the line is overloaded), and the background can also move often, because behind the monitored line is another assembly line, with similar moving objects, in another assembly status.

For an adequate image quality a 5 MP industrial camera was chosen. Finding the ideal camera objective was essential, because of the limited space in the production line area (approx. 1-3 meters). The selected camera objective provides the optimal fit to size of the image as well as the proper sharpness and brightness.

Additionally, a tripod with hydraulic damping and a warning system with both light and sound signals were integrated. These suit the industrial environment and keep the mobility of the system at the same time.

IV. Analysis of the image

According to every data analysis, the process starts with gathering the most available and relevant data. Noise originating from the capturing device is always present, the lighting conditions, shadows or slight changes in positions of the object relative to each other also usually happen. It was a requirement not to train the system in advance, and to reduce operator interactions to the minimum, so the system has to start up and operate automatically. The system needs to model the whole world from scratch, but it may learn adaptively, utilizing as many procedures as necessary to reach the desired response quality.

The information that could be used were that the products were rigid bodies, they moved with more or less constant velocity (on a production line) and the operator had to set up two frames giving some hints about the expected product size and possible position passing by on the production line.

Another constraint was formed by the lighting conditions: the factory was equipped with fluorescent lighting with a 50Hz flickering frequency, and it was not allowed to use additional illumination because of labour safety reasons. The given low intensity illumination limited the video frame rate to a maximum of 10 fps.

Given the above described conditions, it was decided using the robust optical flow algorithm to track specific feature points in the video sequence (Fig. 1.).

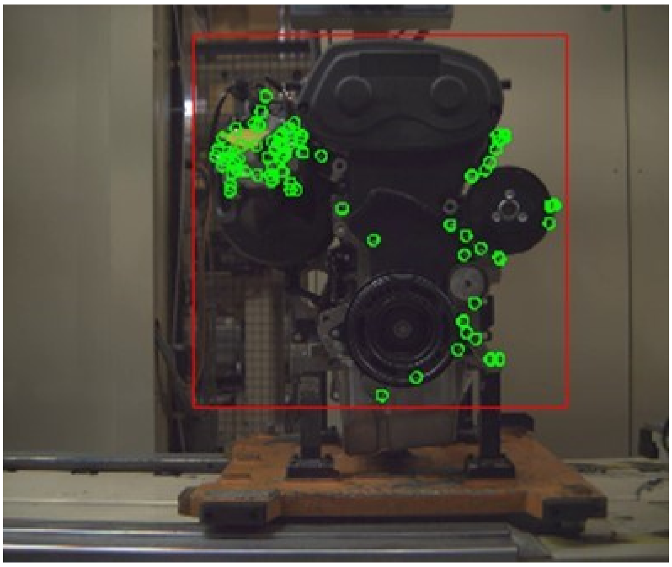

Fig. 1. Product (combustion engine) recognized on the production line by the optical flow of feature points (green circles) and the bounding box of the product (red rectangle).

As no predefined models were given, either from the background or form the product, a system was needed to collect a few data at the beginning, prior to the evaluation of possible defects. After a few products passed through a statistical image model can be built up for both of the background and the product. Lacking an apriori model of the product the same is needed for the products: separate them from the background, align the determined product image to the previously captured ones, and build a statistical model for it.

V. Failure detection Algorithm

After the model for both the background and product has been established, a single detection procedure is working as follows: detecting characteristic feature points; filtering them based on the velocity constraints; if enough feature points found, draw a bounding box around them; pass these points to the optical flow algorithm to track them. To avoid mixing all these different product views into a single model, a few positions were fixed at which the captured images are analysed, and the models are built separately. The newly captured product image at a certain position is then aligned precisely to the product model at that position, and screened for differences.

In a general production environment, the background is not homogeneous, there might be other moving objects, workers, blinking/flickering lights behind the assembly line, and the color of parts of the background can be very similar to that of the product to be investigated. Obviously a black object cannot be detected in front of a similarly black background. Melting the masks from the different viewpoints yields the maximal consensus mask, which will cover the object at any position (Fig. 2.). The hypothesis was to neglect changing shadows, as they were rare, and in a specific position on the production line the object together with its shadows appeared typically in the same way.

The next step is the major goal of the solution: fault detection. Similar difficulties were faced to the object identification process: the lack of fault model or fault definition. In this case the situation was even worse it was required to detect faults that were rare and unusual in any sense, there was no typical size or position of the defects. In this case a statistical pixel based comparison could be performed as “novelty detection”.

The defect recognition of very complex products, however, resulted in new difficulties. Parts of the product can be placed in different, equally acceptable positions: coloured wires in a cable harness or some moving or rotating parts of the product. After collecting enough data (evidence), the statistical model would accommodate to these circumstances locally. A single Gaussian model e.g. can handle such a situation for the price of loosing the sharp accuracy of the defect recognition locally. This approach opens the opportunity to apply unsupervised modelling techniques, like Principal Component Analysis (PCA). Unfortunately, PCA cannot be used in advance, as one might have catch such variability combinations in the first few products (and make a projection onto their hyper-plane).

Now the problem description is complete: without external intervention (fixing background or applying additional illumination) to the measured scene, lacking the model of background, and the model(s) of the products, furthermore lacking the model(s) of possible defects, the system should automatically build all these representations and utilize them to capture defects of the different products.

One question arises immediately: what distinguishes a defected item from a different type of product compared to the models of the previous products? The procedure is based on the heuristic assumption, that the errors are rare, and to get two or more basically identical but defective product images has a low probability. Still, it is unknown in advance, if a new type of product has arrived on the line or the regular one had a fault. In case of rigid bodies, the shape of the products can be compared supposing that exactly the same shape necessarily belongs to the same type of product. The effectivity of all these measures largely depends on the reliability of the underlying data, e.g. how precisely is possible to derive the same feature points in images of two identical items taking the changing environmental circumstances into account, too.

Once a procedure yielding acceptable product type separation is established, it allows to build individual statistical models for fault detection of each type, and also to further increase the quality of type separation.

VI. RESULTS

In the tests of the system, carried out in the production line area, particular segments of the algorithm were being analysed during promoted special events.

Based on the test results, the system runs stable, the first phase thus accomplished, failures with the minimum size of 2% of the whole image were located. Other rarely occurring known failures were produced and detected which have no influence on the proper working, but have a risk later if repaired by the customer (Fig. 2.).

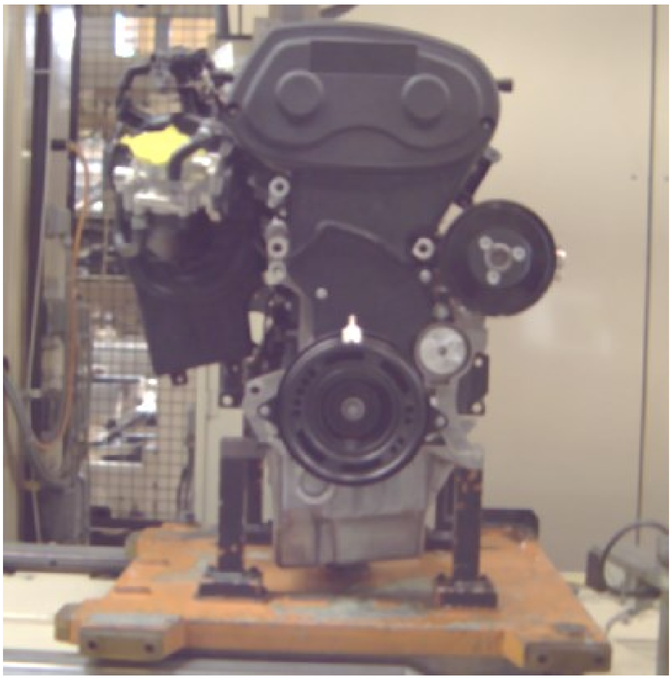

Fig. 2. Inducing a possible failure: a small key placed on a product.

The related software platform developed for the system is user friendly and easy to understand (Fig. 3.). Moreover, it makes possible to review a formerly detected fault, which may be just a change in the model, and if needed add them to the base model as an update, consequently, continuous knowledge extension is allowed.

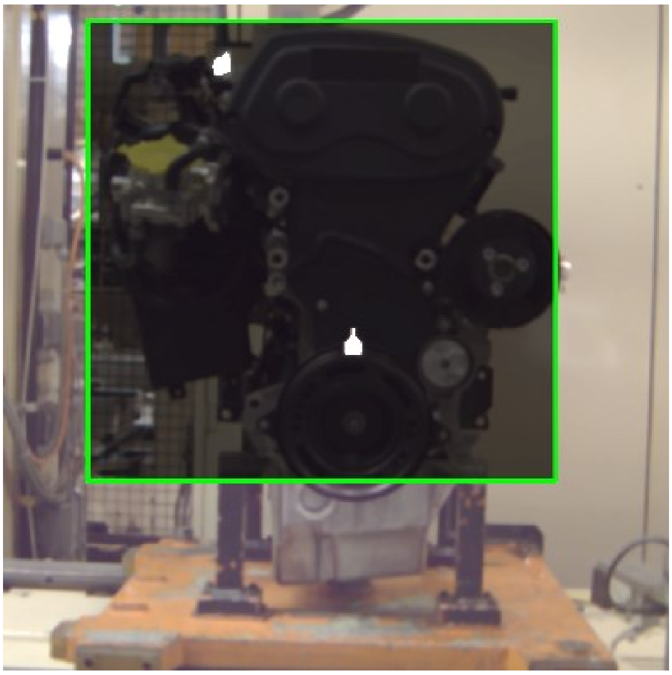

Fig. 3. Results of the fault detection, the key outlined in white.

VII. CONCLUSIONS

The paper presented a vision based, statistical learning system for fault recognition in industrial assembly environment. The literature review of vision systems' applications in industrial quality control mirrored that many camera based solutions are applied in production plants but used typically for detect special, in advance prescribed failures that may occur frequently. The introduced novel solution is addressing the other segment of production failures that are not frequent and without pre-specification in advance. Another significant difference is in relation to the camera working conditions, the quality checking solution should work in changing lighting conditions, without any fixed position and without any field or product specific preliminary given knowledge, consequently learning capability was required. These expectations drove the research to discover and develop a generally novel solution for vision based industrial quality checking.

The system works as expected, and is reliable in fault detection, it requires minimal operator intervention, installation is quick and no expert skills are needed. Failures with the minimum size of 2% of the whole image were located and novel, promptly arising failure of such type is possible to detect with the proposed solution.

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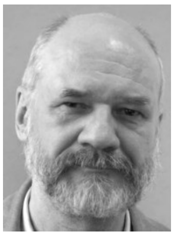

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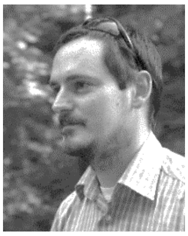

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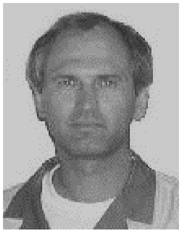

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