AUTOMATIC SURFACE INSPECTION IN STEEL PRODUCTS ENSURES SAFE, COST-EFFICIENT AND TIMELY DEFECT DETECTION IN PRODUCTION *

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Abstract

Here we present the HiNSPECT, a brand new machine based on shape-from-shadow technique, which aims at detecting defective areas on flat and round surfaces with high accuracy within the zero-defects tolerance policy. Special lightning and innovative algorithms concur to highlight the defects on the base of their 3D content. Irregularities, such as bumps or holes, can be neatly seen in real-time without the need of reinspecting offline: small defects have been correctly located on high-resolution images of hot/cold materials and promptly displayed to the operator.
Keywords: Defect detection, high-speed surface inspection, steel production, optical systems, artificial intelligence.

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1 INTRODUCTION

Optical inspection for high-speed steel products eliminates the need for costly off-line checks, thereby increasing productivity.
By leveraging the shape-from-shading concept, we further developed the HiNSPECT with a new periodical defect detection algorithm, an innovative long defect algorithm and an improved surface defect detection method.
These innovative techniques allow an effective and real-time marking of every type of defective areas with a high match rate.
The application of HiNSPECT within the production process allows an accurate control of the production both during the production phases themselves and finally with the quality certification.
In this paper Danieli Automation introduces the new HiNSPECT series by applying artificial intelligence (A.I.) developed for a detailed defect classification.
To meet the growing demands of production monitoring, Danieli Automation has developed an artificial intelligence system to be added to the pyramid-based classification system on the company's level 2 automation system.
The pyramid-based classification system based on HiNSPECT data performs quality control by layers, from the "coil" level to the "heat" level, correlating the final defects with each process (melting, casting, rolling, etc.)
AI technology is the starting point to implement virtuous cycles of continuous improvement in technology-assisted production processes, in line with the principles of Industry 4.0.
AI can be used for a series of necessary, but time-consuming tasks, usually performed by operators and quality management.
Thanks to AI technologies, these activities can be greatly reduced, which will free up the quality manager's time for other activities.
Results are promising if compared to state-of-the-art techniques: holes or bumps as small as 0.3x0.3 mm on round bars can be neatly detected. Long and cyclic defects can be timely marked and displayed to the operator on the pulpit.
As explained before, information coming from machine vision is sent to artificial intelligence for further classification and quality management. The quality manager can continuously match product quality features to previous production operations thanks to the L2 pyramidal classification.

2 OPTICAL INSPECTION

High-speed optical inspection systems can increase productivity by providing in-line real-time defect mapping in rolling mill plants, thus eliminating costly off-line human inspection.
The information provided by Surface-Inspection-Systems (SIS) is of paramount importance to track the final products together with an assessment of their quality, and to decide whether or not a given product is suitable for sale to a given customer.
It can also monitor any significant changes in product quality that can be traced back to problems or weaknesses in the process or machines, especially if the defects are correctly classified.
Well-established approach for detecting defects in long products is based on eddy-current sensors [5], whereby any surface discontinuity caused by the defect alter the circulation of eddy currents. Unfortunately, this approach has been proven to work for short defects only (mostly for transversal defects), whereas it cannot reliably detect

long defects since they cause steady-state patterns in eddy current circulation that cannot be easily distinguished from the "background" effects, due to the nominal shape of the rolled product.
However, current trends in surface inspection of hot products use technologies able to provide more detailed information as opposed to just 2-dimensional surface data.
Unfortunately, conventional 3D laser-based sectioning techniques are not viable because of the high speed of the material, which would lead to prohibitively high sampling rates.
A promising technique that can meet most of the requirements for fast and accurate 3-D imaging of fast-moving objects and guarantee a large depth of field, is the shape from shading approach [1].
This technique relies on the difference in apparent brightness of pixels in the image, to determine the orientation of the physical surface these pixels belong to. The reader may refer to [4] for a detailed survey.
Similarly to shape from shading, photometric stereo approaches utilize reflection models for estimating surface properties from transformations of image intensities that arise from illumination changes.
Shape and reflectance properties of an object are recovered using multiple images taken with a fixed viewpoint and variable lighting conditions [6].
Albeit photometric stereo is an interesting and well-known technique, it is not necessary to recover the full shape of the bar, but only its main surface asperities in an unconstrained environment.
For this reason, we do not provide a model for known lighting conditions, nor do we investigate the presence of a single point source of light in each image. Nor is it necessary to ensure the regularity of the surface that is imaged, relaxing the photometric stereo constraints, and adopting a lighter version of the shape from shading problem.
Other state-of-the-art computer vision solutions essentially focus on differences between brute-force and pixel-wise, or, in case of more refined but computationally expensive techniques, edge extraction [2] or wavelet operators [3].
None of these methods are immune to a significant amount of false positives and false negatives, which translates into false alarms and unseen defects, mostly due to sensor noise, hardware misalignments, bad illumination conditions and other external factors that affect the images.
The visual system has to satisfy two concurrent requirements: rapidity and accuracy. Finding real-time defects as small as a tenth of a millimeter on a surface of a bar running at one hundred meters per second is a challenging task; algorithms must be lightweight and effective at the same time.
Today, customers are not only asking for real-time defect detection but also for defect classification.
Danieli Automation chooses to send information coming from the pseudo 3D defect detection system to an artificial intelligence neural network that can classify the defects detected previously for complete quality management.

3 DISCUSSION

3.1The HiNSPECT system

Danieli Automation patented the HiNSPECT system to analyze the surface of wire rod and rolled bars during the hot rolling process, with the goal of automatically detecting any surface defects on the tested product.
The existing HiNSPECT setup is based on high-power LED lighting and high-resolution acquisition sensors, which localize and identify surface defects, both delimited and diffuse on bar, such as seams and laps, slivers and scabs, cracks (originating in the conticaster) and periodical marks (essentially caused by rolling problems).

Figure 1. Installation of a HiNSPECT wire rod application

3.2Defect detection process

HiNSPECT uses the following basic general detection process:

- **Sensing:**Acquisition of a defect-related signal, in our case an image with 3D information thanks to the double angle lighting system.
- **Segmentation:**The defective area, in the acquired image, is segmented from the background and other non-significant artifacts.
- **Feature extraction:**Measurement of the geometrical properties of the surface discontinuity, to be used for basic machine vision classification (basic classification).

From this point the HiNSPECT system knows that in the segmented area there is a surface unevenness (that could be considered as a surface defect in the majority of cases in the rolling mill process).
At this stage the information provided by HiNSPECT is used for the L2 classification SW to monitor the production.
The advanced HiNSPECT A.I. package checks for and classifies defects, providing the final quality index for the product.

- **Post processing – L2 production classification engine:** The L2 classification criteria makes the proper decisions based on the output of the basic HiNSPECT classification or the advance classification A.I. and process characteristics (for example, a piece is scrapped if the number of defects exceeds a given limit).
- **Advanced classification:** The first stage of artificial intelligence analyzes the image from the shape from shading machine vision algorithms (the basic package output of HiNSPECT) and eliminates the detection of false positives. The output of the first layers of the neural network are only images in which the presence of at least one defect is certain.

  The second layer can classify defect types and learns from the data coming from the whole HiNSPECT installed worldwide.

3.3HiNSPECT sensing and segmentation

The basic principle of optical 3D defect detection is that surface discontinuities (3 dimensional defects) alter the reflection pattern of light.
By illuminating the object from different directions, the defects can be detected by a camera.
To obtain 100% surface coverage, several cameras and a ring of solid-state light are arranged in a modular way around the product.
A number of images of the object are taken from the same viewpoint, but with different illumination sources.
The optical system exploits light from different directions which potentially highlights surface discontinuities by our shape-from-shading technique; the latter estimates surface shape from a camera image using variations in the observed brightness across that surface.
In practice, two images, representing incident light from angulated illuminators, are acquired: at the same time, on the same geometrical position on the bar and processed by means of computer vision algorithms.

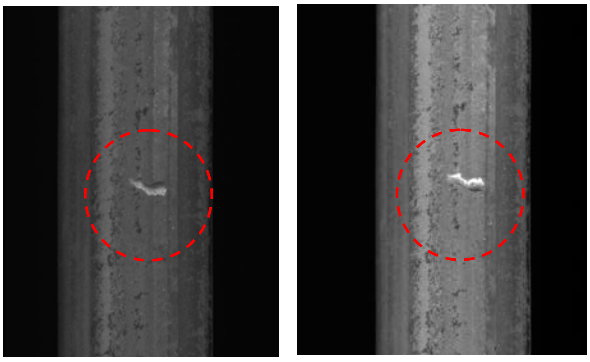


Figure 2. (left) Different directions of light, “different” images of the same defect
Figure 3. (right) Thanks to the processing of the previous images only the real defect is highlighted and recognized

3.4HiNSPECT detection process schematic

HiNSPECT senses images of the product with different light angles.

Thanks to shape from shading tecnicque only real surface unevenness is segmented by proprietary image recognition algorithms.
Data are immediately sent to the rolling mill operator for production checking.

Figure 4. Detection process of advanced HiNSPECT package

3.5HiNSPECT application at a glance

HiNSPECT is used in the metal industry with two fundamental objectives:
1) **Real-time production monitoring:** the operator is informed in real time of any rolling mill problems such as overfill, scratches or periodical defects due to broken stands.
2) **Production monitoring:**for process improvement and final certification of production in order to have reliable feedback on the production cycle.

3.5.1Real-time production monitoring

During normal production operations, the system is used to monitor any problems. Shown below is the detection of a periodical defect and the historical trend. This information is made available to the operator in real time so that he can act quickly to change the rolling mill setup.

3.5.2Production quality and certification, advanced classification formula for coils and heats

With the aim of continuously improving the production process, the possibility of monitoring the “coil quality index” makes it possible to establish a correlation between the production processes and final product quality.
A comprehensive formula that can be customized according to the customer’s real needs, is used to automatically classify each billet individually.
This formula considers:
1) Defective area related to the overall product surface
2) Presence of a single defect with a surface area greater than a customer defined threshold
3) Presence of long defects (scratches, overfill, overlap, etc.)
4) Presence of periodic defects (broken rolling stand or a marking pinch roll)
5) Total number of coil defects (overall number of defects increases with the wearing of the rolling stand)
The formula is configured for different steel grades.
Likewise the classification used for the single coils a classification formula for the heat is used.
Each single coil classification is used for overall classification of the heat.

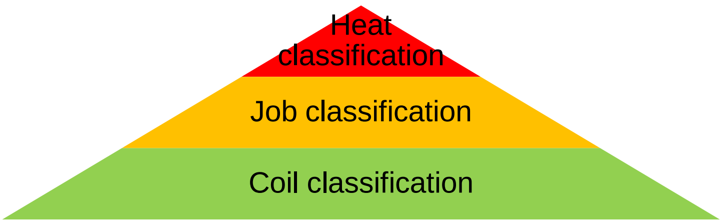


Figure 5. The production classification pyramid

Below the **first level** of the L2 classification interface. On the coil level every single coil is classified according to the criteria described above in the “classification formula”.
The **second level** of classification is the Job level.

Every single Job is classified according to the quality index of the Coils. It's possible to have a statistical description of the quality index of the coils in order to classify the job with different criteria.
The **third level** of classification is the Heat level.
Every single Heat is classified according to the quality index of the Jobs. It's possible to have a statistical description of the quality index of the Jobs in order to classify the Heat with different criteria.

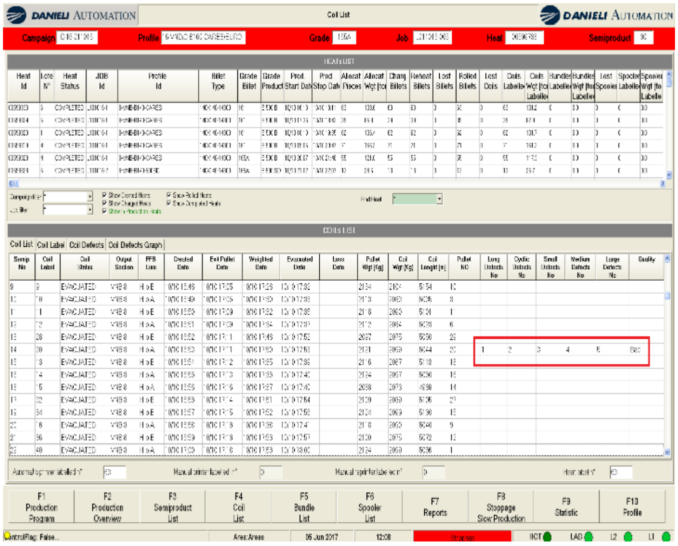


Figure 6. Classification of production, **Coil level**

3.6A.I. Neural network classification - Neural network architecture

Nowadays, customers are demanding more than simple defect detection.
Customers also require classification of the types of defects with a view to full production monitor.
For this reason, Danieli Automation has developed the artificial intelligence package (A.I.) to be combined with the HiNSPECT system and L2 classification criteria.
By utilizing the machine vision detection capabilities in combination with the potential of convolutional neural networks, it is now possible to fulfill this request.
In 2017, Danieli Automation began testing a prototype of a Convolutional Neural Network (CNN) on sample images coming from a single HiNSPECT system.
Convolutional Neural Networks are a category of neural networks largely used in image recognition and classification.
These networks are applied not only for generic classification but are also involved in localizing the position and the dimension of every object into image.
Against a sliding window-based brute force approach where the proposal network slides over the CNN feature map at each window, outputting N potential bounding boxes and scores, we use a more efficient architecture.
The network being tested predicts each bounding box using the features from all the images in one step.
Basically this technique can drastically improve performance, compared to other convolutional networks like Fast R-CNN.
The architecture of our model consists of a dense fully-connected neural network. This means each layer is connected to the next one and also to all the subsequent layers. This improves the flow of information and gradients throughout the network

and makes them easy to train. These models can have more than 100 fully-connected layers.
After almost 1 year of testing, it has been proven that the accuracy of the neural network is strictly related to the number of defective area samples used for the training. As of now, the number of defective image samples is low since they come from a single plant, but the results are encouraging and led to the further development explained above in this document (i.e. a worldwide, shared defect image database) .
The performance of a neural network is evaluated using an **accuracy index.**
The accuracy index represents the quantitative summary measure of the applied classification model, indicating the percentage of correspondence of the theoretical datum obtained in the phase of the model's instruction with the real datum.
The greater the index (a number between zero and one), the shorter the distance between the measured value and the real one.
It should be noted that the true value is a conventional value, especially since no value can be perfectly known. It follows that the concept of accuracy must always be related to the true value that operators consider "right", by choice, where this choice is motivated by the precision of the work done in the initial phase of annotation and training, a path that enables us to obtain that value.
Today Danieli Automation has verified the grown of the accuracy on an estimation with a training set of only a small amount of samples (some hundred).
It has been shown that what is really needed for training are defective image samples; for this reason, in 2018 Danieli Automation will introduce A.I. cloud computing for defect classification.
This innovation will be possible only thanks to the sectioning of the shape from shading technique to automatically obtain samples for training.
According to the first dataset we obtained follow estimation of the reachable accuracy related to the number of annotated defects images.

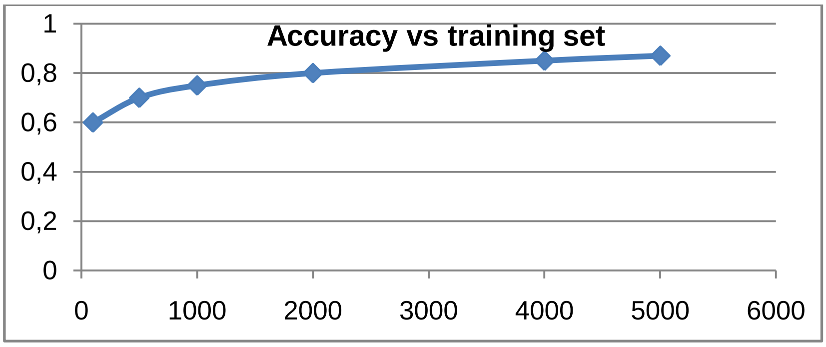


Figure 7. AI accuracy vs number of annotation of training set

3.7Cloud based A.I.

As described above, the HiNSPECT base application software is responsible for processing the input signals and identifying surface unevenness.
Particular attention has been paid to the design of the optical and lighting systems in order to highlight only the defects on the material surface. Right from the image acquisition stage, actual defects are isolated from the background (segmentation).
In the HiNSPECT system, segmentation is done by a shape from shading technique that does not need to be trained by humans.

Spots, material color and temperature do not affect the segmentation and are not part of the learning process.
The defective area features were established during the development of HiNSPECT, based only on the 3D geometry of the defect.
Unlike other systems, which use image elaboration for segmentation, **HiNSPECT does not need to process all the images** after acquisition to detect defects, thus saving time.
Danieli Automation decide to use previous benefits as an aid for defect classification A.I.
Since **only a few images are segmented due to the presence of the defect it is possible to classify remotely via internet connection** (the data flow to remote computing is low).
After the detection of defective areas the information is **automatically sent to Danieli Automation Cloud Computing A.I.** for the analysis of the defective image and successive retraining of the neural network.
The first benefit of the neural network advanced package is the detection of the differences from "normal" surface and is ability to cut the already low false positive detection rate.
The neural network final target is to classify the defect according to the **shared defect database** created by the defective areas from worldwide installations of HiNSPECT. After few seconds customer will find on the HiNSPECT database the precise classification of the image by the type of defect and the real surface area interested by it.

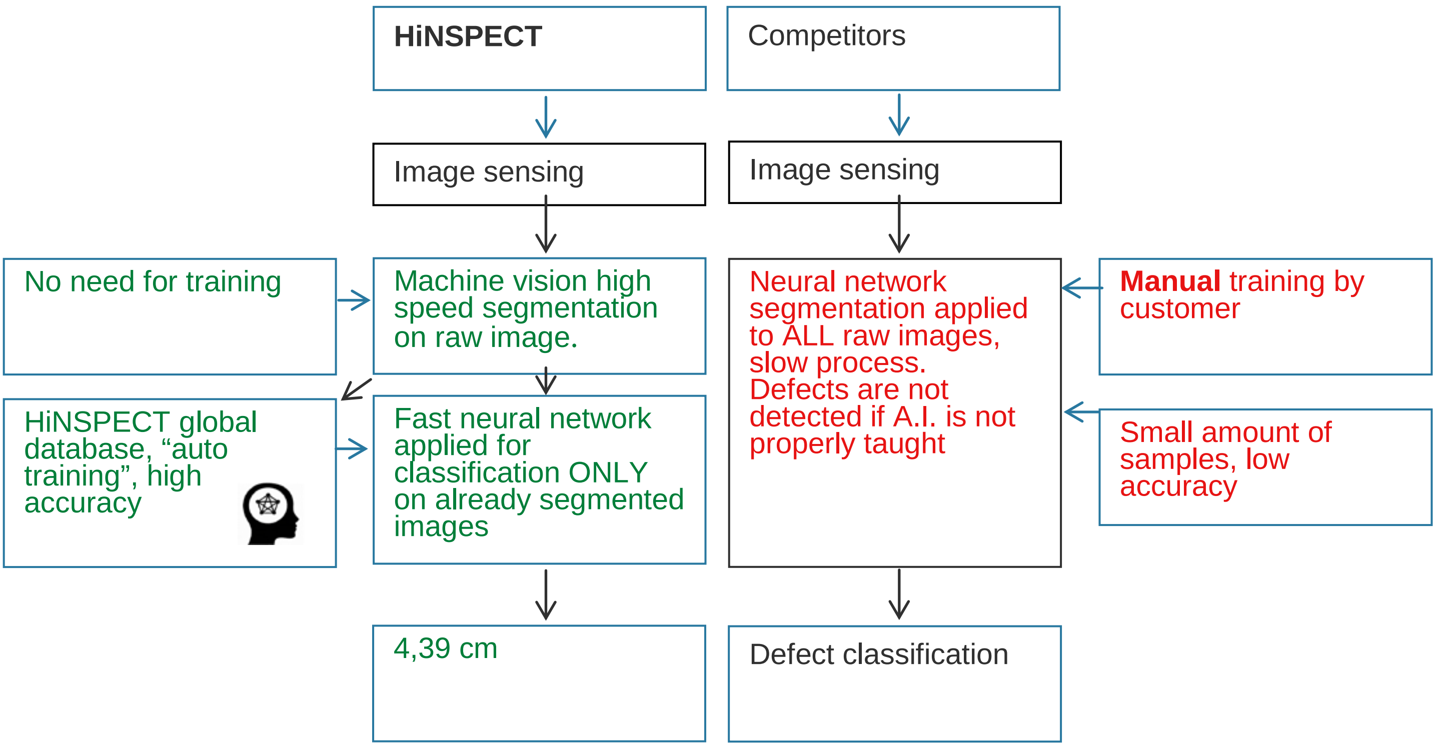
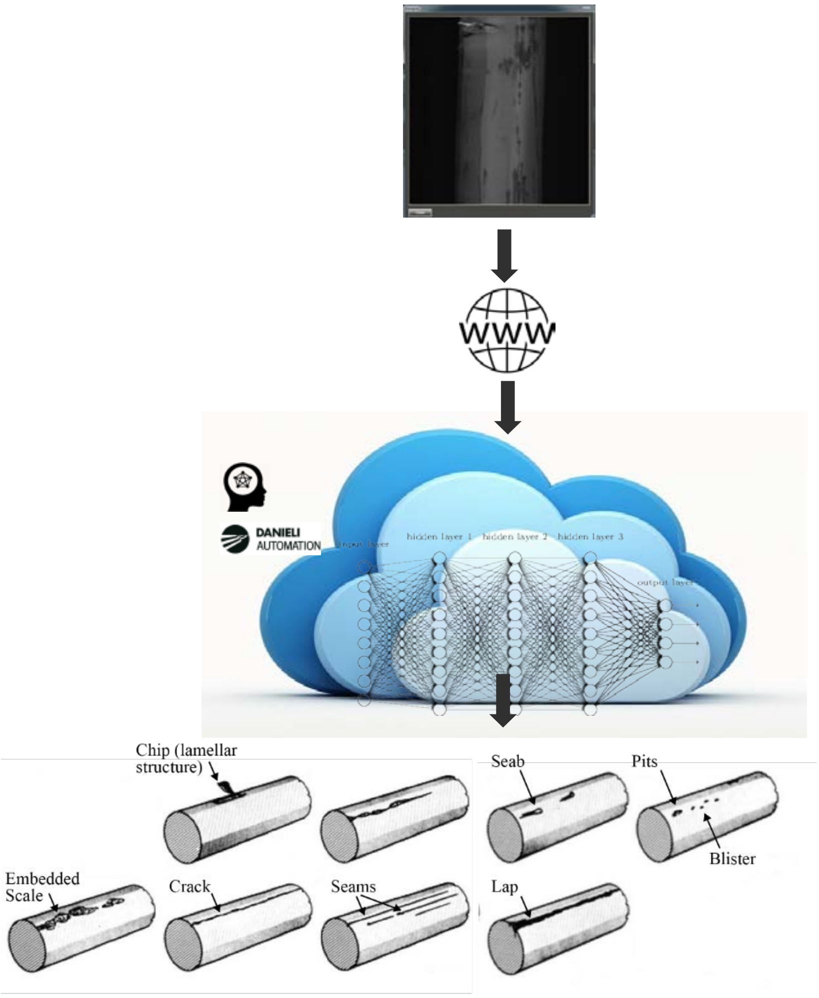


Figure 8. HiNSPECT detection process vs. competitors.

The overall **computation time of defect detection and classification is extremely short.** The detection of defects based on basic package (shape from shading) will be perfectly in real time, the defect image will then be sent via internet connection to the Danieli Automation Cloud Computing center.

The information received from the HiNSPECT, located everywhere in the world, is filtered and classified by A.I. Thanks to shape from shading sectioning, only real defective areas are sent to the Danieli Automation Cloud Computing center for analysis in almost real time . The transmitted data represent only a small amount of the collected data, demanding small internet bandwidth improving reliability and quickness of the service.



Detection by HiNSPECT
HiNSPECT detects defective areas and sends raw images to centralized A.I.

Deep learning artificial convolutional neural network located in D.A facilities, checks the consistency of defect detection, removing all false positives and classifying the defects.

Classification of defects
The classification of defects allows advanced classification of the coils for complete quality management.

Figure 9. Convolutional neural network

3.8Worldwide shared defect image database

As explained in the previous chapter, one of the main pre-requisites for the use of deep learning convolution neural networks is the amount of samples to be provided for training (also called as annotations).
The image annotations collected are used to instruct the A.I. during the training process.
In order to satisfy this real defect image requirement, Danieli Automation has created the Danieli Automation cloud AI and shared the defect database.
The main purposes are:

1) Only real defect images are stored thanks to shape from shading sensing, thousands of images from different HiNSPECT facilities (**). The segmentation is automatic and does not require operator intervention. Only final classification will be checked in order to prepare the next training set database.
2) AI is centralized and could be upgraded more frequently than a remote installation, CNN maintenance operations are costless and transparent for the end customer.
3) The teaching process of the AI and retraining is Danieli Automation expertise duty only and is continuously performed.

4) The customer can join the Danieli Automation A.I classification service with a simple annual subscription. No need to invest in dedicated HW and no initial development costs.

(**) Note that Danieli Automation is committed to protecting the privacy and confidentiality of information provided by the customers who use the A.I classification service. Danieli Automation anonymously collects and processes (it is not possible to trace the image source once it has been acquired by the system) all the data of defective samples coming from worldwide HiNSPECT facilities. Danieli Automation will undertake not to disclose customer information to any other third parties. This Danieli Automation cloud computing has security measures in place with the aim of protecting the loss, misuse or alteration of the information.

Figure 10. Centralized AI and image database

4 CONCLUSIONS

Exploiting an improved version of the renowned shape-from-shading technique, the HiNSPECT employs high-resolution cameras and solid-state light to spot defective areas on round products with superior accuracy, ensuring safe, cost-efficient and timely defect detection in production.
Special hardware, dedicated firmware and groundbreaking high-level machine vision algorithms have been carefully blended to provide a unique machine, designed to work on hot or cold round products.
Results are astonishing if compared to state-of-the-art techniques: irregularities, such as bumps or holes, can be neatly seen in real-time with their pseudo-3D depth.
Small defects of less than 1mm2 have been automatically located up to a rolling speed of 120m/s.
The classification of all the products is done thanks to the high "good match" detection rate from HiNSPECT. The L2 based product classification is based on geometrical defect features (area).
The classification criteria use the quality classification of a single coil (calculated with a specific formula that determines not only if a defect is present but also other key factors) to completely monitor production quality up to the job/heat levels.
In 2017, Danieli Automation developed the first "deep learning CNN" applied to defect classification in order to give the added value of a typological defect classification.
Now, defect severity is determined not only by area but also by typology.
L2-based production classification SW is now more reliable and “intelligent”.
The coil classification formula now also evaluates the type of defect and not only the relative defect area or defect quantity.
The first test on the AI resulted in an accuracy that was strictly related to the number of training samples.
Accuracy increases in proportion to the number of training sets.

Through our simulation, it is possible to achieve with an asymptotic-logarithmic trend an accuracy level of 0,85 with a training set of at least 5000 annotations (for each kind of defect).
The innovation of 2018 will be the introduction of Danieli Automation Cloud A.I., where defective area images are sent to Danieli Automation's cloud computing center.
In the A.I. center, data are subjected to a further false detection filtering and classification of the defect, sending back to the customers results of the analysis in almost real time.
Thanks to the existing shape from shading machine vision techniques only real defects are sent for classification so the amount of data sent by the internet connection is reduced, making it possible to use a no demanding internet VPN connection.
The huge amount of worldwide defective samples collected by Danieli Automation in the "Worldwide shared database" can be profitably used by Danieli Automation expertise for the training and periodical re-training of the neural network.
In this way, training is quick and cost-free for the final customer as it benefits from a pre-taught neural network without any need for dedicated HW in the plant.
Worldwide installations of HiNSPECT jointly (and securely) collaborate for the development of the best and biggest defect database in the world.
With the only cost of an internet connection and annual license, customers will benefit of a defect classification service that is free of initial costs, maintenance and re-training of one of the largest surface defect classification artificial intelligence.

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