Quality Control Inspection Opportunities Using Deep Machine Learning Technology

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ABSTRACT

Consistent compliance with quality requirements of the product becomes the key to the sustainable competitiveness for food producers competing in domestic and export markets. More and more markets become so quality sensitive that even a small number of defective product packages might lead to recalls of the whole batch and damaged relationship with clients. It is especially true for Japanese and South Korea markets. While the source of non-compliance might be any production process, including all upstream processes before packaging, improved quality inspection systems at the end of the production line to eliminate non-compliant packaging becomes extremely important. In this paper, a machine vision system was developed for quality inspection of the packaging to visually identify contamination and quality of sealing and label by the smart camera to detect the visual non-compliance. The vision system consists of an inspection camera for capturing the image of the package and an image analysis software with Machine Learning capabilities to identify misplaced, missing and damaged labels or sealing problems.

The inspection system achieved necessary functionality and precision - only 0.5% of contaminated end sealing packages with particles longer than 1 mm were allowed, speed of inspection - up to 100 packages per minute, time to reject - the time from bypassing the scanner to the rejection - max. 400 milliseconds.

Further development of system accuracy and speed using Machine Learning reached 120pcs/minute and continues to increase while requiring less time and labour than existing inspection methods.

Keywords: Quality control, Machine Vision, Machine Learning, package inspection

1. INTRODUCTION

Machine Vision in Food and Beverage Industry is one of the most sensitive industries for package defects. Food safety, improving productivity and quality while being low cost is the problematic goal to complete for food and beverage manufacturers around the world. Usage of the Machine Vision inspection systems in the industry enables to detect the defects of packaging and to remove them in any production phase. Inspection of the packaging at the end of the production process not only ensures that only compliant product reaches the client but also the number of rejected packages after packaging reveals potential systemic quality issues in the upstream production process.

It creates an opportunity for the producer to address production process issues before wasting raw material, human resources and energy to produce a non-compliant product.

Though an industrial camera that captures images and analyses the captured images through Machine learning algorithms and takes action and extracts real-time and customised reports. According to the VDMA Organization, In German and Europe, the machine vision in industry sales records more than doubled in the years 2005 – 2015. In the last ten years, the turnover of the German machine vision industry has doubled. Between 2013 and 2017, the machine vision industry grew by an average of 13 per cent per year. According to current surveys, the VDMA expects the record level of 2.6 billion euros in 2018. Applying Machine Vision leads to improved quality, greater reliability, increased safety and cost-effectiveness [1]. Machine vision can interpret as many data, verify and process then transmit the results to the systems of the value chain in every phase of production. Technologies are moving from electrified to automated, to digitalised manufacturing, such as big data, autonomous robots, IoT, cybersecurity and augmented reality are transforming the manufacturing landscape.

Previous studies have shown that vision systems can be used to analyse to estimate the quality of surfaces, detect defects and damage, and estimate physical properties [2]–[5]. For instance, a camera and hardware-based image analysis system was able to inspect of up to 120 pcs/minute with the width of the package - 150 mm (minimum width of the package - 100 mm) and length of the package - up to 300 mm.

A vision system was developed to non-compliance of packaging (sealing and labels). Therefore, the objectives of this research were to develop a quality control system to ensure compliance with the requirements of quality standards of every market.

2. SPECIFICATIONS OF ENVIRONMENT

A vision system was developed for Spaghetti pillow packaging using a flow-wrap packaging technique.

Packaging process consists of the following steps:

1. Product preforming - product is formed and aligned into the boxes
2. Product cutting - spaghetti is cut into the length for packaging

3. Product wrapping - product is wrapped in the tube around the preformed product. Fin seal is made.
4. End sealing - the tube is sealed between packages
5. Cutting - sealed packages are separated by cutting the sealing between packages

Packaging seals packages using the heat (Fig.1).

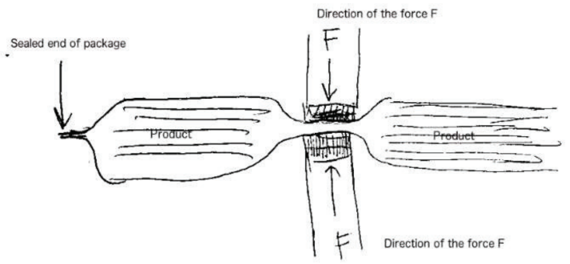

Figure 1. Flow-wrap packaging technique

The label on the plastic wrapping material is printed with the jet printer before the packaging process and currently is scanned with the camera immediately after the printer, five packages length earlier before the packaging process. A machine vision system was developed for quality control process to expose contamination of sealing and label inspection by the smart camera to quantify the detected inconsistencies.

Sealing control report
An existing control for sealing ("as is"):

- The sensor measures the thickness of the sealing at the end of the package. Measurement is taken at the time of the sealing, before cutting between packages.
- In case if the thickness exceeds a set threshold value, two packages are rejected. Even in case if only one package is defective.

The existing system was hard to set up: the too-high threshold value and many defective packages were passing the test (FALSE-NEGATIVE) error. Too low and too many good packages were rejected (FALSE-POSITIVES). Also, such an approach does not detect contamination by small pieces or when contamination evaporates at the time of the sealing.
Final sealing quality was not inspected at all. Previously, if final sealing were damaged, then the package was passed to the customer. Fin seal damage is a critical quality issue.

Label control report
An existing control for the label ("as is") - the label is printed on packaging material for every package using VideoJet jet printer before packaging. The use of the label is increasing because larger labels allow producers to adapt the product to different markets without ordering different packaging design. Basic information printed on the package is related to the safety of the product and traceability - best before date, production time/date, batch number. However, via label information, it is possible to customise the product for different markets, additionally printing content, allergen information, distributor, in particular, country, etc..
Overall previous manual inspection was labour-intensive, costly and less efficient. Further, the accuracy of the defect detection was lower due to vigilance issues (see Signal Theory in Ergonomics) regarding human errors.

Quality inspection elements
The quality inspection shall be made to inspect packages visually to eliminate visually defective product. Therefore, complexity of the label is increasing. Existing OCR (optical character recognition systems) for label inspection is very difficult to use, due to different languages, fonts. The importance and complexity of the label on the package are increasing, therefore the quality of the label is an important part of the packaging (see example in Fig. 2)

Figure 2. Example of product using flow-wrap packaging

In order to fulfil quality goals, the following elements for inspection were determined:

- Inspect all features of the package after the packaging process.
- Inspect fin seal in full length
- Inspect end sealing visually for contamination and holes
- Inspect end sealing for excessive wrinkles, occurring when sealing is done with excessive heat.
- Inspect the presence and quality of label from below—language and font agnostic visual inspection against the template.
- Reject package only deemed to be low quality

3. SOLUTION

R&D process included tests with two camera setup as depicted in figure 3. The system hardware consisted of a transport trailer, machine vision cameras, a host computer for image acquisition control (#5000 Processing unit) and data processing.

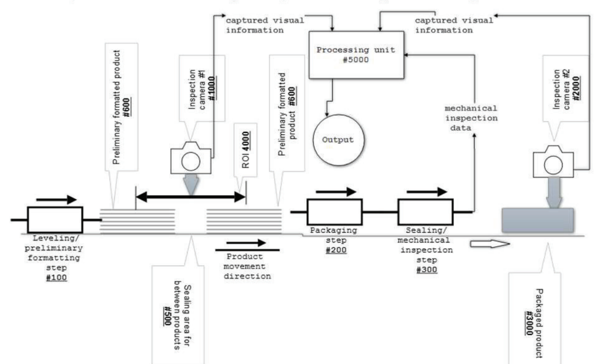

Figure 3. Schematic of Machine Vision system for detection of contamination of sealing and label inspection.

Hardware control modules, controlling line scan cameras
Hardware control modules, controlling high-speed machine vision light controller, controlling lights allowing multiple pictures in one scan with different light and camera settings. Data collection module on the factory floor for ground picture collection to improve the system. Integrated annotation and quality evaluation system, capturing current results of the inspection together with the original pictures collected. Annotation system is set on the cloud for external annotators to be able to:

- Annotate new original pictures
- Estimate the quality of quality and precision of the existing system
- Annotate new artefacts on the pictures
- Export ground truth data for training new weights for neural networks

System management module, allowing to separate different modules and their dependencies, meanwhile connecting them in one system. Containerisation approach allows using different frameworks, languages and dependencies on the same computer, isolating every execution environment

Solution for sealing

Contamination of the sealing was measured by the force of the pressure on the sealing (Fig 1). The problem is that small size contamination does not increase the thickness of the sealing and might be passed. By increasing sensitivity sensor starts to reject packages with thicker sealing where are not particles. If packages are rejected, then two packages are rejected as the sensor cannot sense to which package contaminated sealing belongs—creating an excessive amount of rejected product.

Solution for labels

The initial process of the inspection was not satisfactory. Either the print is perfect - pixel on pixel bases, or it is rejected. Current inspection process does not take into account that size of the printed label along the direction of movement of the tape varies. Existing inspection did not tolerate such variations. Therefore, most packages were rejected, and the producer did switch this particular inspection.

Operator when setting up the product might pull packaging material bypassing the printer by the length of four packages. Therefore, inspection immediately after the printer might create packages without the label - which is a critical quality issue.

However, camera #1000 was eliminated in the final setup as there was no correlation between the state of the preformed product and the contamination of the sealings. Before packaging step #200 there is empty space where misplaced pieces of the product are dropped out of the packaging process.

Machine Learning

In 2018, R. Ren et al. [6] proposed a generic approach that requires small training data for automated surface inspection. The approach builds classifier on the features of image patches, where the features are transferred from a pre-trained deep learning network. And then pixel-wise prediction is obtained by convolving the trained classifier over input image. The experiment involves two tasks: (1) image classification and (2) defect segmentation. Other studies [7], [8] showed a huge amount of data (Big Data) obtained from many hours of automated video recordings makes it impossible to manually inspect the images and detect surface defects. In the same manner PET quality,

In 2016, C. Huang et al. proposed a method of workpiece recognition and location by Hu moment invariants based on Open Source Computer Vision (OPENCV) [9]. Firstly, the methods of image preprocessing, including image greying, mean filter, image binarisation by adaptive threshold segmentation, are used. And then, the contours from the binary image are extracted. Finally, the object workpiece can be identified by matching the extracted contours with the object contour from the template image by Hu moment invariants. At the same time, the method of confirming the workpiece position and direction is put forward. It showed that the proposed method could recognise the target workpiece and locate the position effectively by the experimental results.

The first approach used was using OpenCV 4.0 where the image was preprocessed, and contamination of the sealing was identified by using binarisation, edge detection and contour finding to identify inconsistencies in the sealing.

First layer was Gaussian Filter; the second was the Canny edge detector, the third was Gaussian Thresholding with Gaussian kernel size of 1/20 of image of the package.

While such an approach was useful to identify most of the defects, number identified edge cases (such as possible sizes, properties (using Hu moments) of contours found, increased exponentially. At the same time, the system still proceeds either too many False positives or false negatives.

To increase efficiency, the system was changed to neural convolution networks. Yolo 2.0 convolution neural network was implemented as an alternative to the series of steps described above. To eliminate noise, the information preprocessing consists of Gaussian blurring filter and building pseudo color image, consisting of two channels. Each channel is image of the sealing captured using different exposure and light. One image is captured using very short exposure time and exposes the structure of the transparent sealing using backlight. The second picture is created using exposure times, where every transparent segment is fully exposed (white), and only the contamination particles are visible. Such an image allows for the neural network to build a weight that takes into account both images and properties of these images.

Therefore, automated detection of defects can help to save time and costs. The advantage of the deep convolutional neural network solution is to skip elaborate procedures feature extractions required in classical learning approaches. The same approach was used in wood defect detection has an important influence on the automation of wood industry [10]

Figure 4. Example of data containing labeled region of interest (ROI) objects of package.

Retraining of the network for the detection of package defects. RGB images were captured the machine vision camera line scan camera at 4000 pixel resolution. Full image therefore is 14000x4000 pixels, where every even line is Creation of ground truth data was performed manually using the MATLAB Image Labeler. Object selection consisted of a box placed around the outer boundaries, data was not stored as image pixels, but rather stored as metadata of defect location corresponding to area coordinates within the specified subset image (Fig. 4).

This metadata was referenced during training. These images were utilised in training and validation of the image analysis program, with 70% (1829) of the images used for training and 30% (780) used for validation. The subset images were randomly assigned to either the training or validation datasets with each image being assigned to only one dataset to ensure uniqueness.

The necessary quality goals were reached:

- Only 0.5% of contaminated end sealing packages with particles longer than 1 mm is allowed. In includes all holes in non-transparent packages.
- Only 5% of contaminated end sealing packages with particles smaller than 1 mm is allowed, when are not visually seen by the naked eye on the packaging line.
- Speed of inspection - up to 100 packages per minute
- Time to reject - the time from bypassing the scanner to the rejection - max. 400 milliseconds.

Results

Speed of inspection - 120 pcs/minute max.

Time to reject - decision by inspection machine is made in up to 350 milliseconds.

Accuracy - in requirements zone.

4. CONCLUSIONS

In food industries, collecting training dataset is usually costly and related methods are highly dataset-dependent. So most companies cannot provide Big Data to be analysed or applied. By the experimental results, the recognition accuracy can be obviously improved in future. To summarise, the development of a machine learning based on machine vision system for defect detection will contribute to technological innovation, industry, national development and other applications. It will increase the economics and productivity of companies. The faster machine vision image analysis system achieved an speed of inspection - 120 pcs/minute max and time to reject - decision by inspection machine is made in up to 350 milliseconds. A further assessment of system accuracy using random images from the deck plate spacing experiments resulted in a high accuracy (6 no 10159) Overall accuracy of the system was most affected by sensor. The developed systems were able to detect 360 of 10159 defects achieving quality goals and necessary accuracy/precision.

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