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Computer Vision for Manufacturing Industry Applications

Coordination



- High productivity and quality by intensive inspection
- High production speed and large flexibility urge to automated defect detection
- In weaving sector, inspection is performed at the end of the manufacturing stage
- In the clothing industry, defect detection is performed between manufacturing stages
- In both cases, carried-out by manual measurements and visual examination of markers and texture

Computer vision systems can offer:

- robust detection
- large flexibility
- does not suffer of human limitations
- could entirely replace traditional methods

Automated visual inspection relies on material properties as texture, shape, color or other features

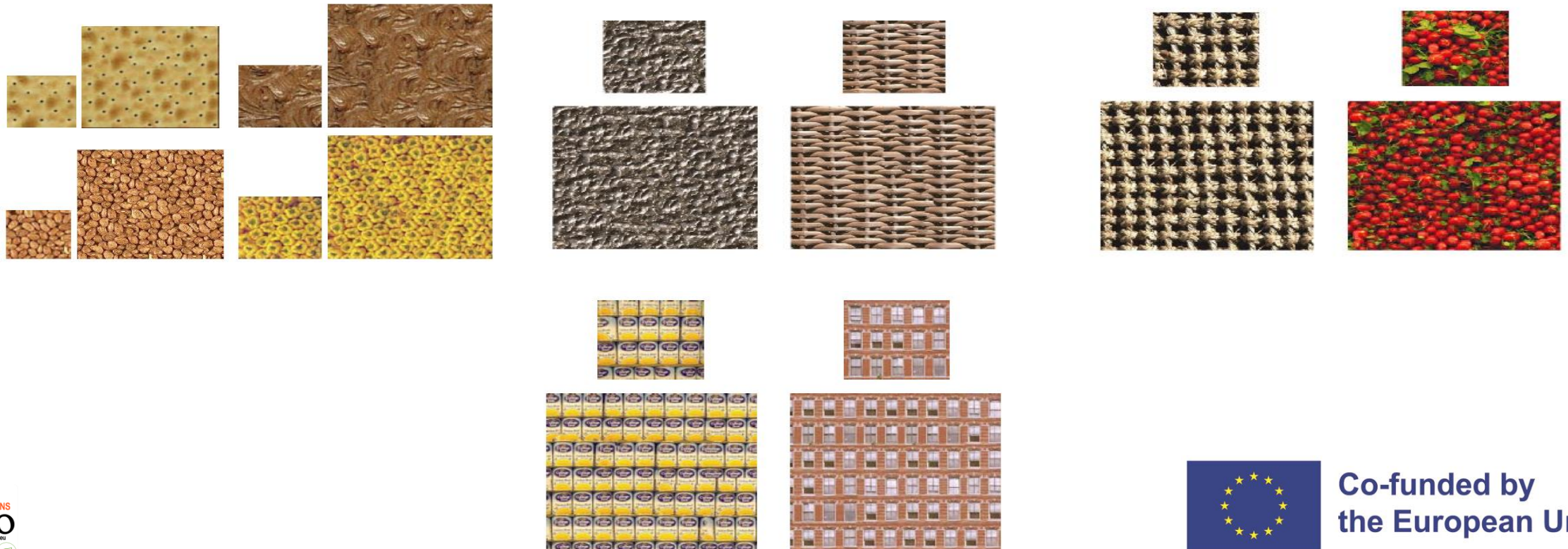
Image Processing for Textile Defect Detection

Why texture?

- Quality assurance systems have been developed in the aim of providing the client with a high level of trust in the producer's capacity
- Automatic production control is an important phase of quality assurance
- Texture analysis techniques for fabric defect detection
- Image processing for sewing defect detection

What is texture?

- “Texton” – the texture unit
- Replication of the texton in two directions -> frequencies
- Detect frequencies -> detect the texton



The basics

Texture analysis techniques for fabric defect detection are based on:

- gray-levels texture properties, texture statistics
- characterization of fabric texture using a Markov random field model
- detection by model-based clustering
- Fourier transforms and Fourier-domain analysis for discriminating texture variations
- multi-resolution approaches by decomposing fabric images in several scales using a bank of Gabor filters
- Convolutional Neural Networks (CNNs) as the current standard for feature extraction
- pre-trained models on large datasets and fine-tuning them on specific industrial defects

The basics

- Defined as mathematical representation of the receptive cells of the visual cortex
- Applications starting from edge detection, ending by texture classification and image compression
- Feature detection characteristic of the Gabor filters relies on the possibility of tuning the orientation and his frequency selectivity
- A bank of Gabor filters processes the input image
- Choosing the appropriate filter represents the key to correct results

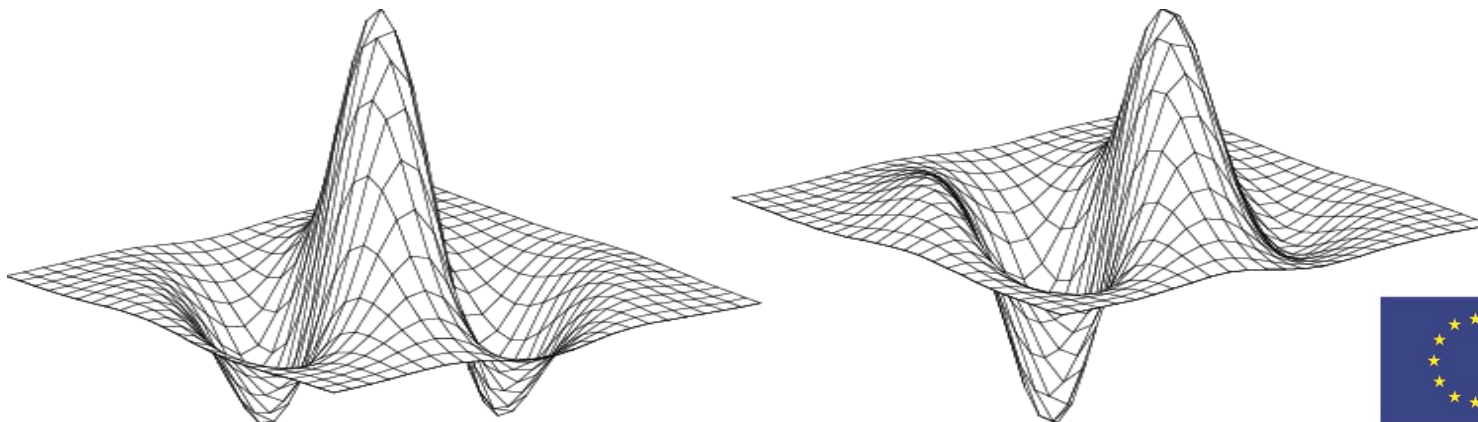
The basics

- Gabor function resulted from a modulation product of a gaussian and sinusoidal signals
- The Gabor function has the following general form:

$$f(x, y) = \frac{1}{2\pi\sigma_x\sigma_y} \exp\left[-\frac{1}{2}\left(\frac{x^2}{\sigma_x^2} + \frac{y^2}{\sigma_y^2}\right)\right] \exp(2\pi j u_0 x)$$

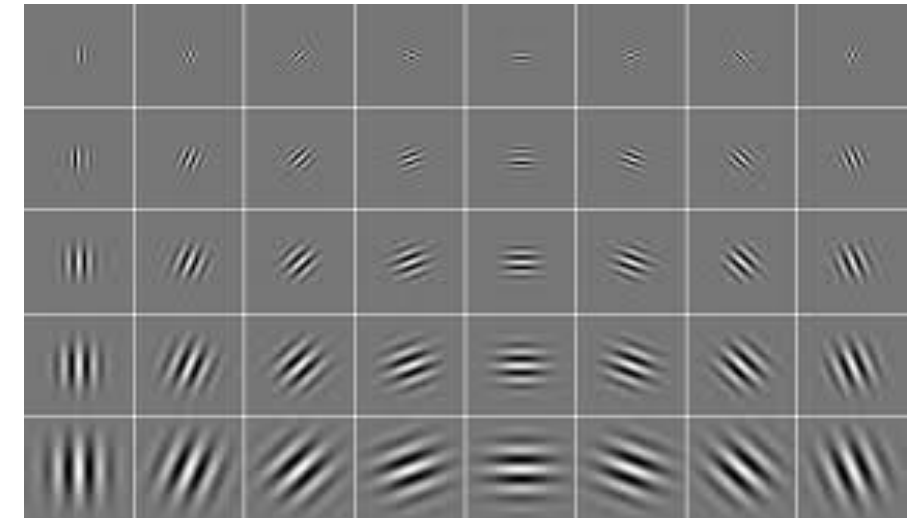
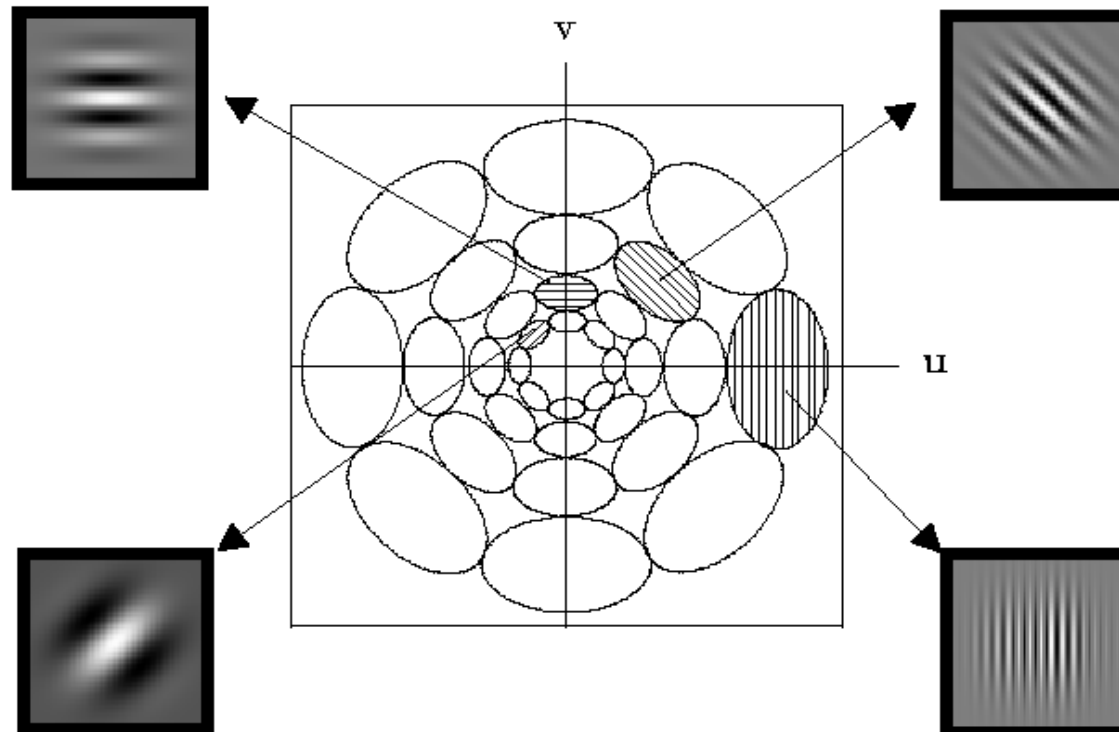
where u_0 - radial frequency of the filter

σ_x, σ_y - constants defining the gaussian envelope



Algorithm

- Feature detection characteristic of the Gabor filters relies on the possibility of tuning the orientation of his frequency selectivity
- Create a filter bank (variations in orientation and frequency)



Algorithm

- Choosing the appropriate filter from the bank
- Using an unsupervised algorithm for filter selection
- The filter with large output for defect texture and small output for defect-free
- A cost function for the discrimination of the filters bank results

Steps

- Computing S x L filters in a M x M matrix form
- Dividing the original image I(x,y) in N regions of k x k pixels
- Applying each filter in the bank to the each of the N regions
- Computing the average result for every ith filter for region n in N

$$A_n^i = \frac{1}{k \times k} \sum_{(x,y) \in n} I_{pq}(x, y)$$

Steps

- Retaining maximum and minimum average value for every i th filter among the N regions
- Computing the cost function as the normalized difference between the two values

$$C(i) = \frac{A_{\max}^i - A_{\min}^i}{A_{\text{ref}}^i}$$

- Selecting the filter having the highest cost function
- Re-filtering the original image with the selected filter
- Thresholding operation for the final segmentation of texture defects

Results

Test images:

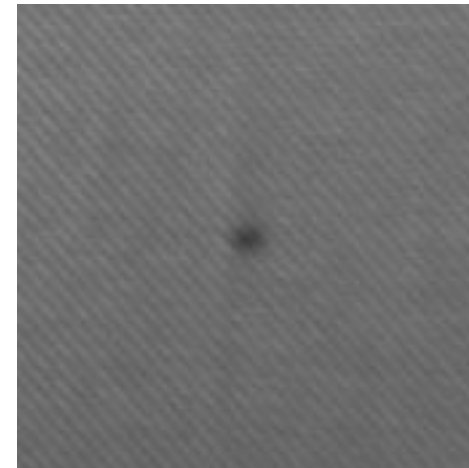
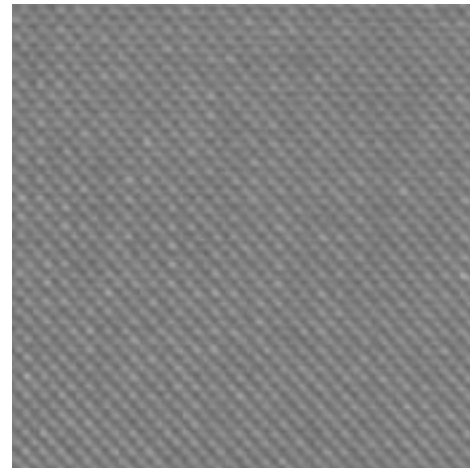
- Images from the Brodatz set and acquired in ULBS Vision LAB
- Airbag fabric images from the TAKATA-Petri production site

Bank of 24 Gabor filters (4 scales and 6 orientations)

Filter size of 9 x 9 and images partitioned in 32 x 32 regions

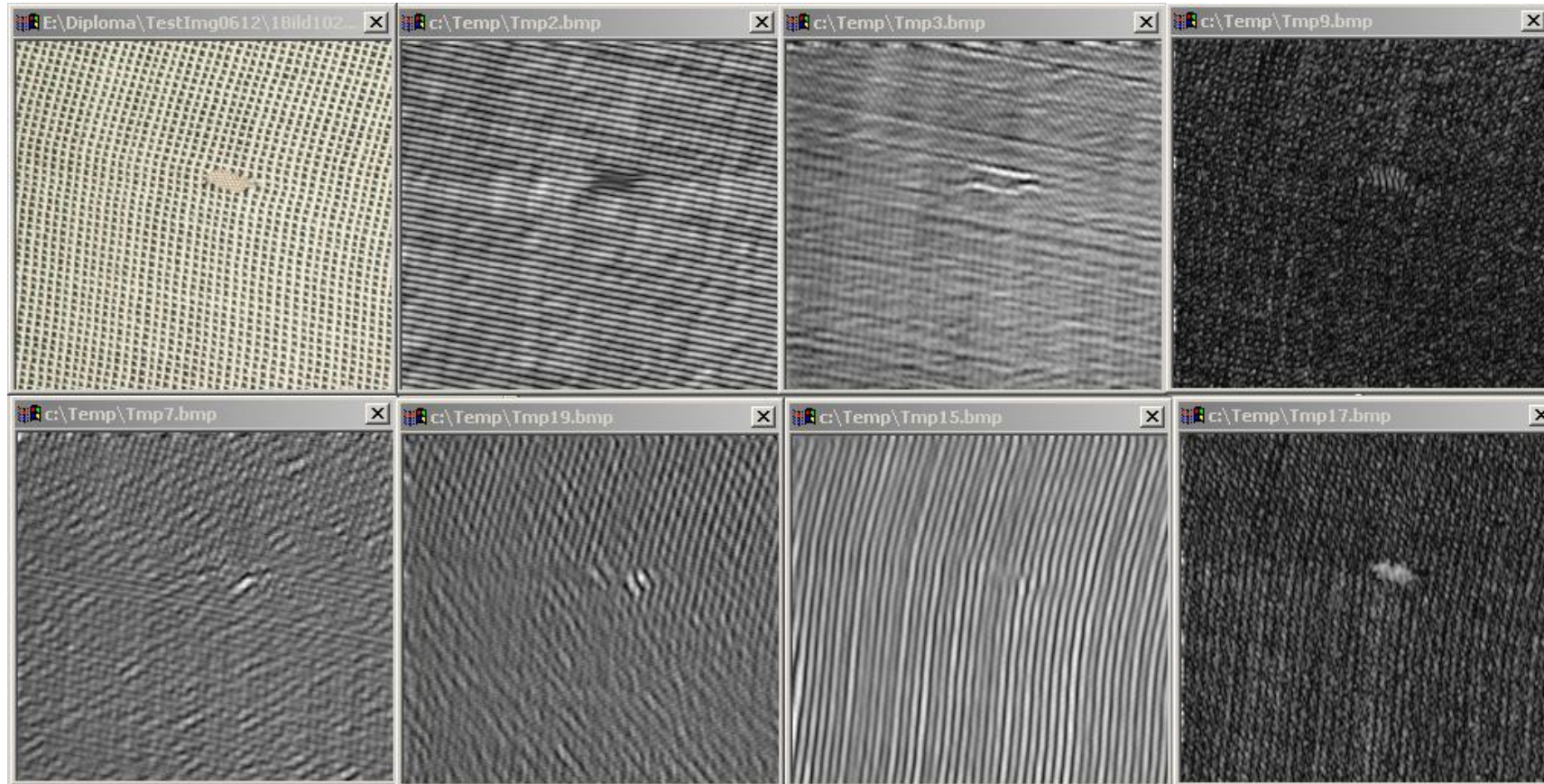
Defects considered:

- break-out
- thick-yarn
- mispick
- dirty-yarn
- stains



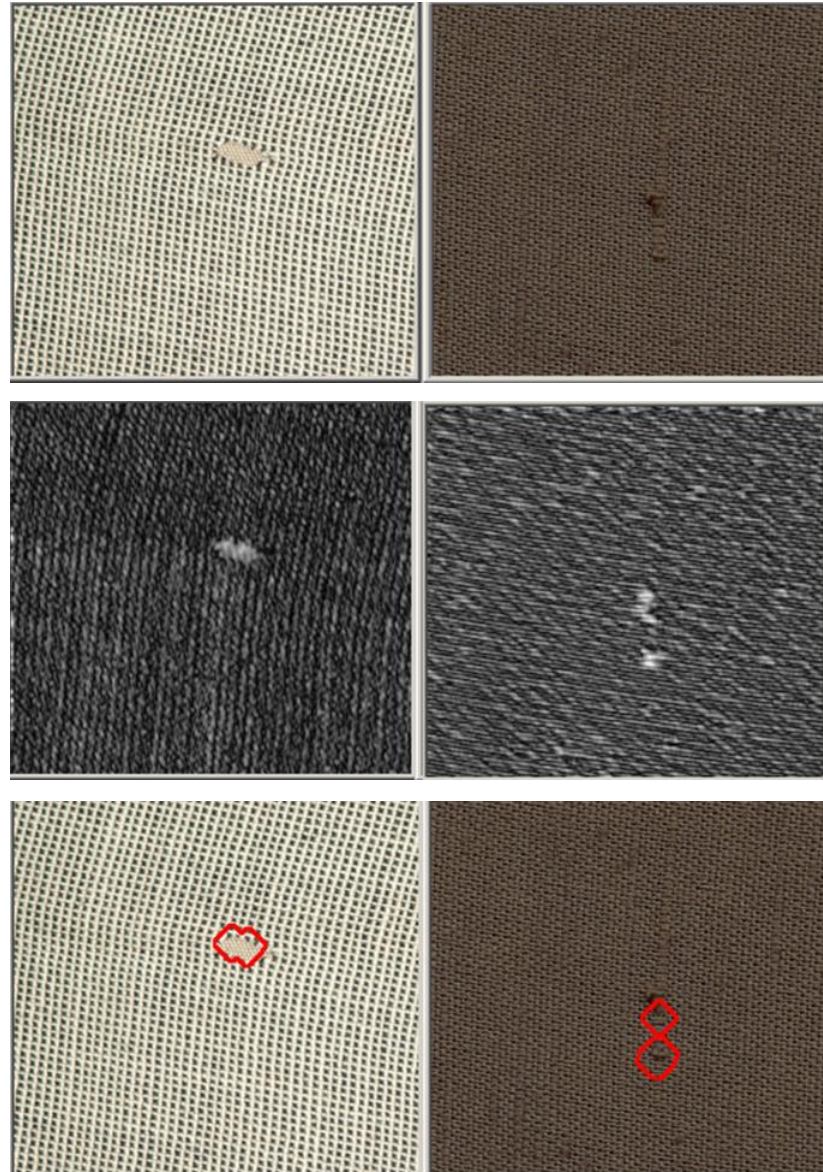
TEXTURE ANALYSIS TECHNIQUES FOR FABRIC DEFECT DETECTION

Results



TEXTURE ANALYSIS TECHNIQUES FOR FABRIC DEFECT DETECTION

Results

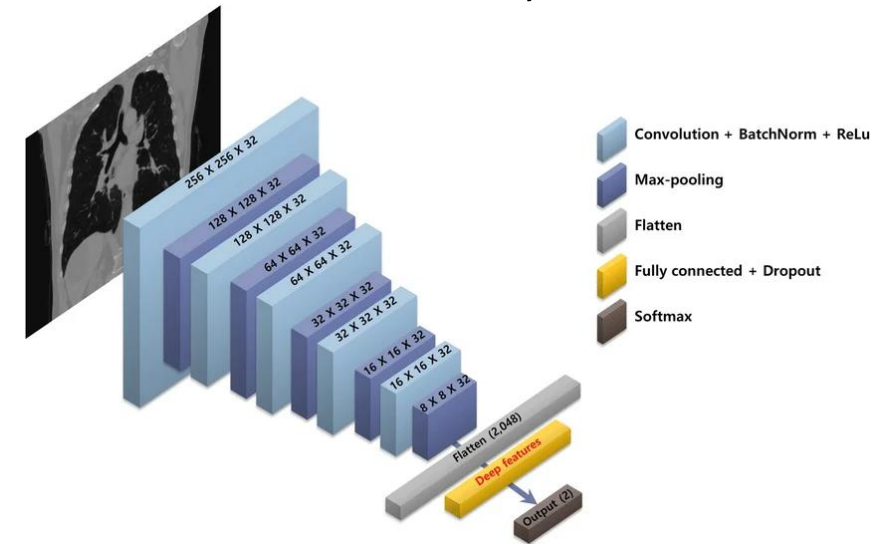


BEYOND GABOR FILTERS: THE SHIFT TO DEEP LEARNING

- The Traditional Approach: Relies on manual filter selection, such as a bank of 24 Gabor filters (4 scales and 6 orientations) to detect specific texture variations.
- The Limitation: Manual tuning and "choosing the appropriate filter" from a bank is the key to results but requires significant domain expertise.
- The Deep Learning Solution: Convolutional Neural Networks (CNNs) replace manual selection by learning the optimal filters directly from the data during the training process.
- Key Advantage: While Gabor filters are mathematically predefined to represent visual cortex cells, CNN kernels evolve to identify the most discriminative features for specific defects like break-out or mispick.

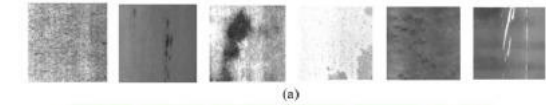
BEYOND GABOR FILTERS: THE SHIFT TO DEEP LEARNING

- Feature Hierarchy: Just as your current system uses multi-resolution scales, CNNs use layers to build complexity:
 - Lower Layers: Detect basic edges and textures (similar to Gabor filter outputs).
 - Higher Layers: Combine these textures to recognize complex defect patterns in airbag fabrics.
- Spatial Invariance: CNNs excel at detecting defects regardless of their position on the loom, improving upon traditional window-based partitioning.
- End-to-End Learning: Eliminates the need for separate steps like "unsupervised algorithms for filter selection" and "cost function computation".

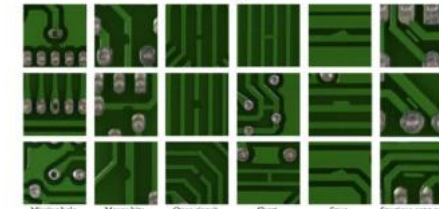


BEYOND GABOR FILTERS: THE SHIFT TO DEEP LEARNING

- Leveraging Pre-trained Models: Instead of starting from scratch, use models trained on millions of images (e.g., ResNet, VGG) and fine-tune them for textile defect detection.
- Hybrid Approaches:
 - Augmentation: Use Gabor filters as a "preprocessing" layer to provide the CNN with high-quality initial texture features.
 - Refinement: The CNN then learns to ignore noise that might otherwise trigger a "thresholding operation" error in traditional segmentation.
- Improved Accuracy: Better handling of complex cases like stains or dirty-yarn where simple frequency selectivity might fail.



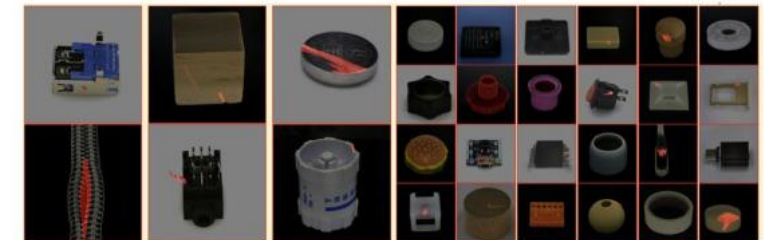
(a)



(b)



(c)



(d)

Implementing a Defect Detection System in Airbags Manufacturing

A DEFECT DETECTION SYSTEM IN AIRBAGS MANUFACTURING

ULBS Research Grant for Takata Petri Sibiu,
Romania, actually Joyson Safety Systems



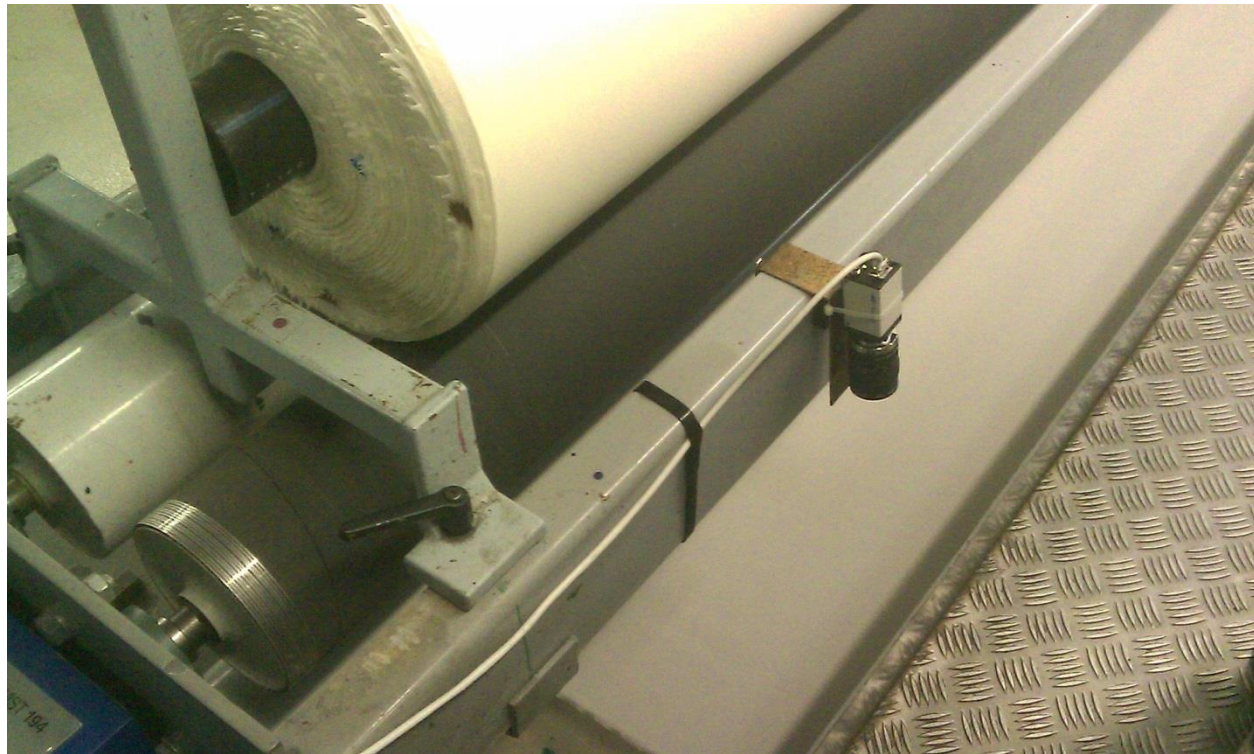
- Improvement of quality assurance techniques
- Weaving is one of the most important stages in airbags manufacturing process
- Quality of fabrics must be higher and provide a low air permeability in order to prevent structure tear or hot gas leak in the inflation process



A DEFECT DETECTION SYSTEM IN AIRBAGS MANUFACTURING

First steps

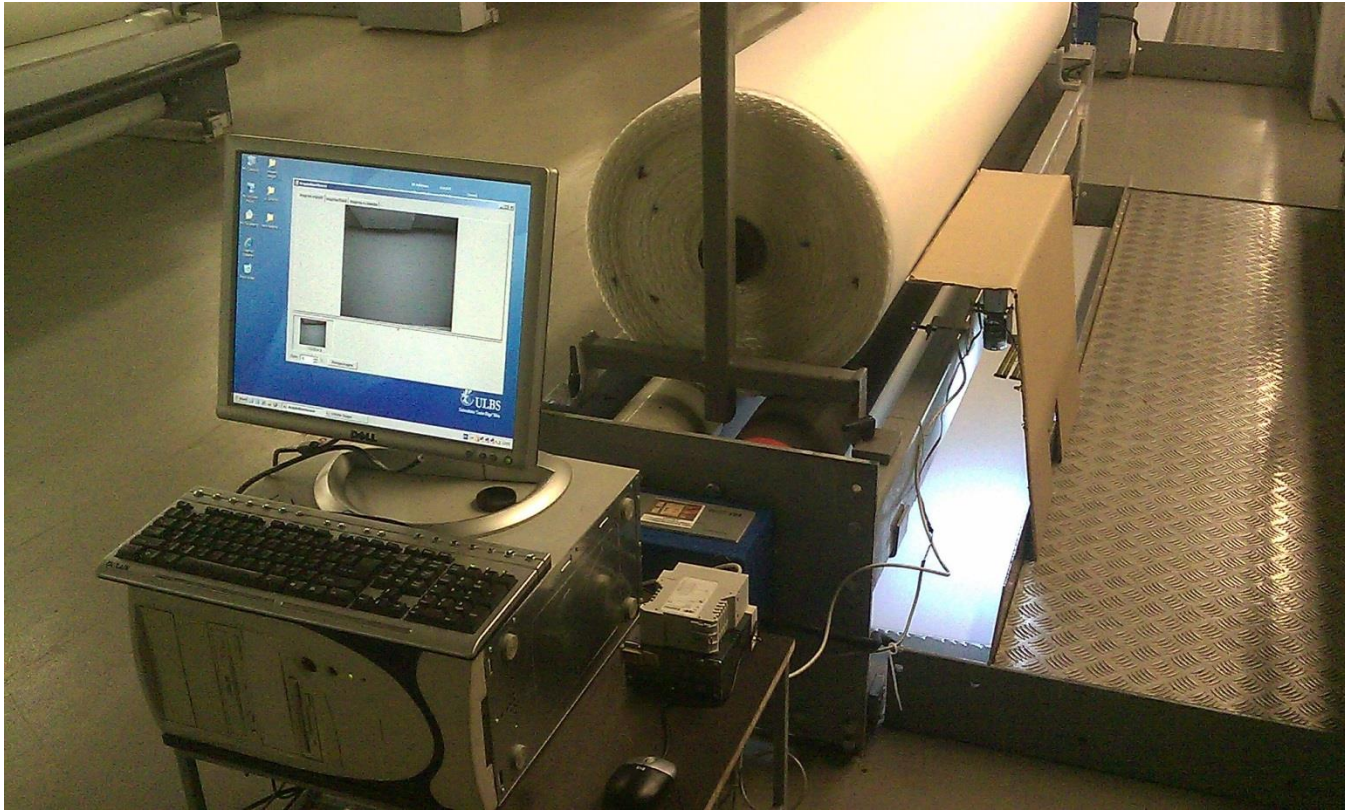
- Started with one camera on Toyota water jet loom
- 5MP Gibabit PoE Industrial camera



A DEFECT DETECTION SYSTEM IN AIRBAGS MANUFACTURING

First steps

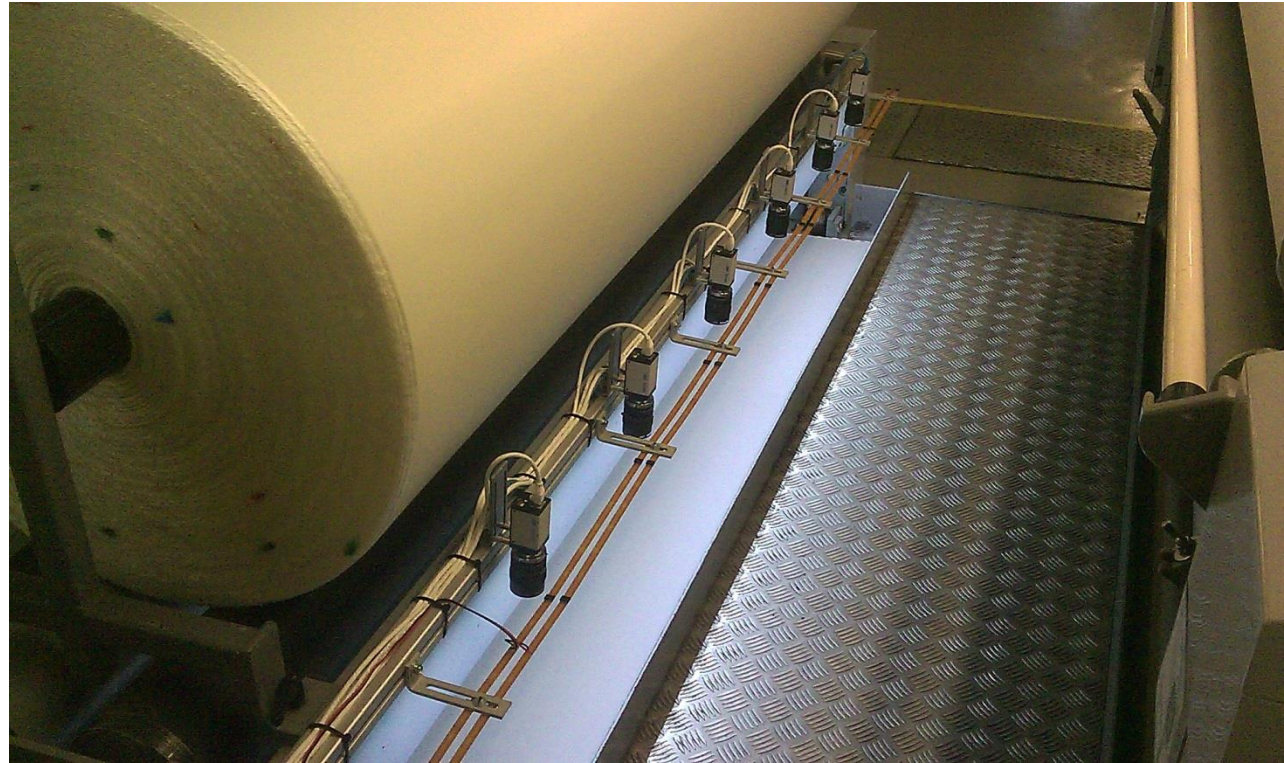
- Adding local illumination and lighting immunity



A DEFECT DETECTION SYSTEM IN AIRBAGS MANUFACTURING

Implementation

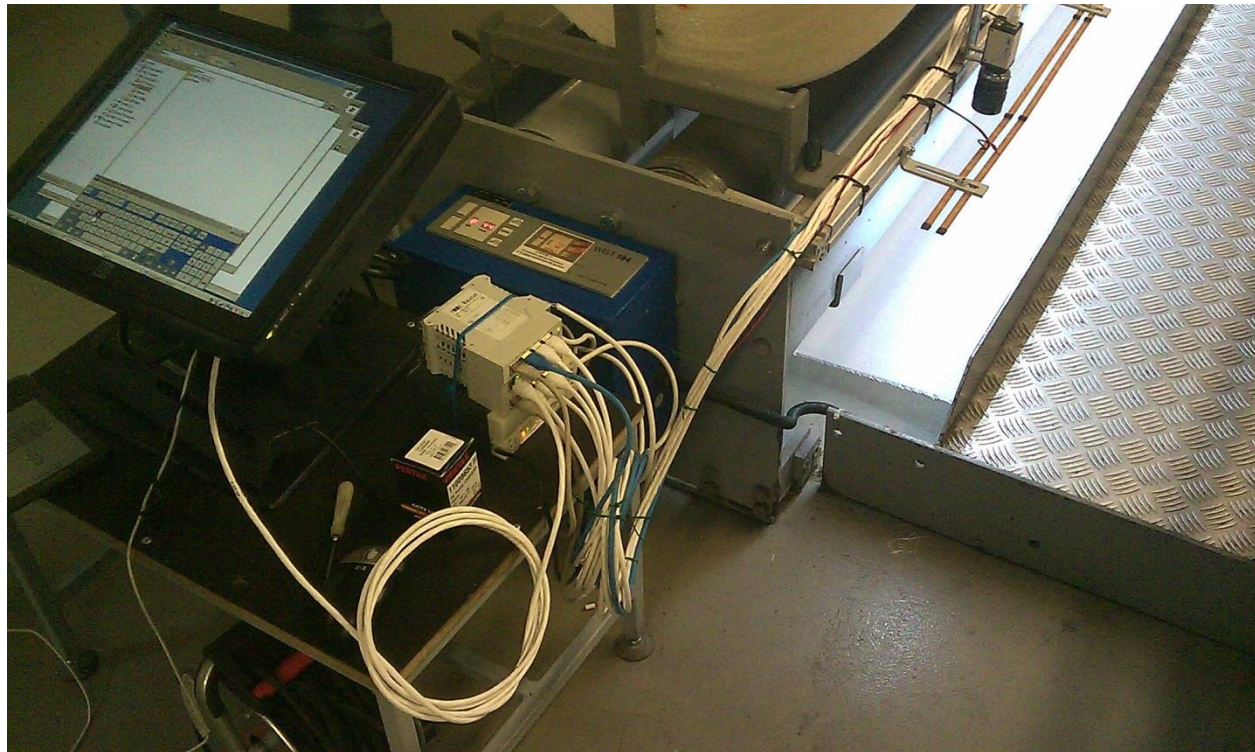
- One more step ahead
- 6 GigE cameras and double LED illumination



A DEFECT DETECTION SYSTEM IN AIRBAGS MANUFACTURING

Final implementation

- Improved application for defect detection and touch screen operation
- Dedicated server for data analytics



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A DEFECT DETECTION SYSTEM IN AIRBAGS MANUFACTURING

Final implementation



Conclusions



- The system was not implemented on all 60 looms for on-line defect detection (!)
- It was used for an analytical study on the defect causes -> loom maintenance
- A reduction of less than 0.5% defects by applying customized and scheduled loom maintenance
- Better results and less costs!!!

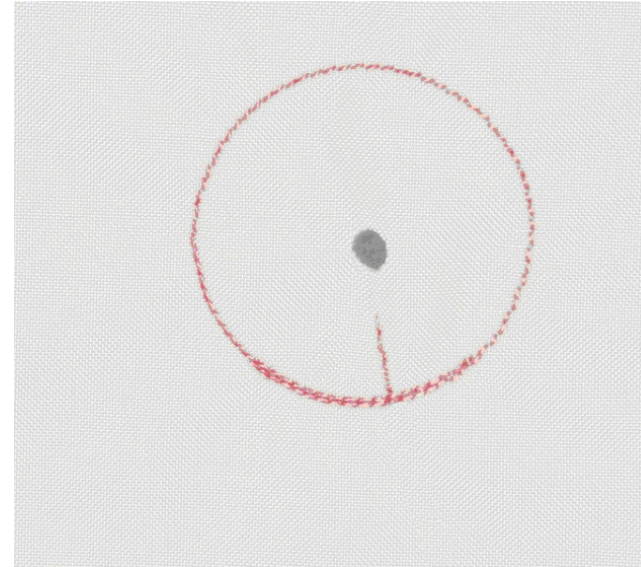
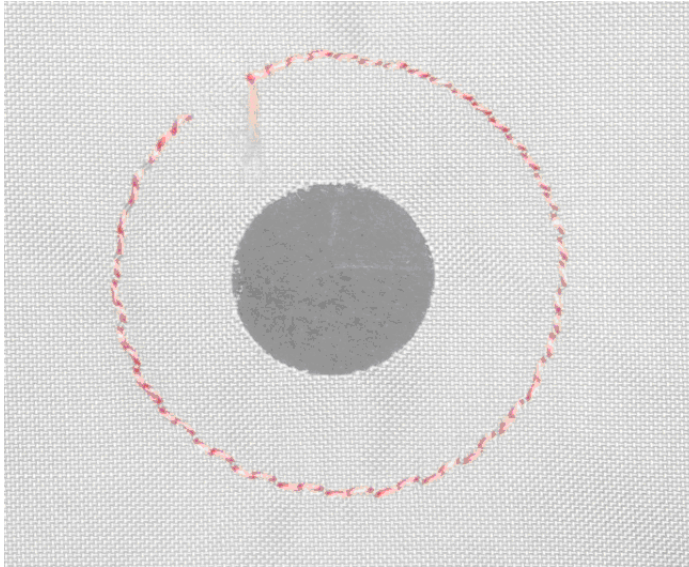
Image Processing for Sewing Defect Detection

The problem



- Airbags are subject to strict quality control in order to ensure passengers safety
- The quality of sewing influence the final product
- Sewing defects must be early and accurately detected
- Airbag seams assembly can take various forms, linear and circle primitives, with threads of different colors and length densities, creating lockstitch or double threads chainstitch
- A framework for the automatic detection of defects occurring during the airbag sewing stage
- Types of defects as skipped stitch, missed stitch or superimposed seam for lockstitch and two threads chainstitch

Examples



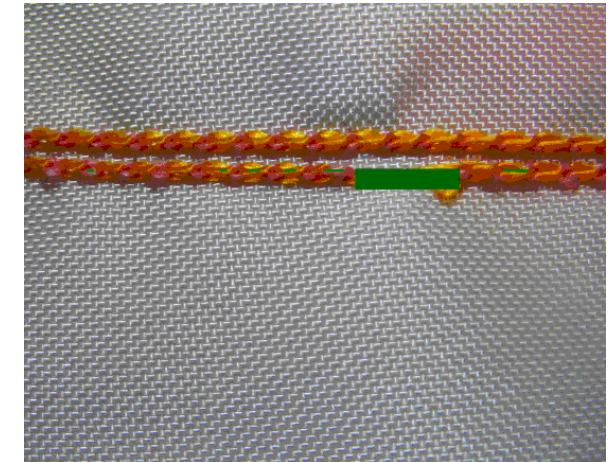
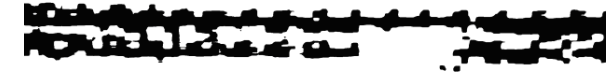
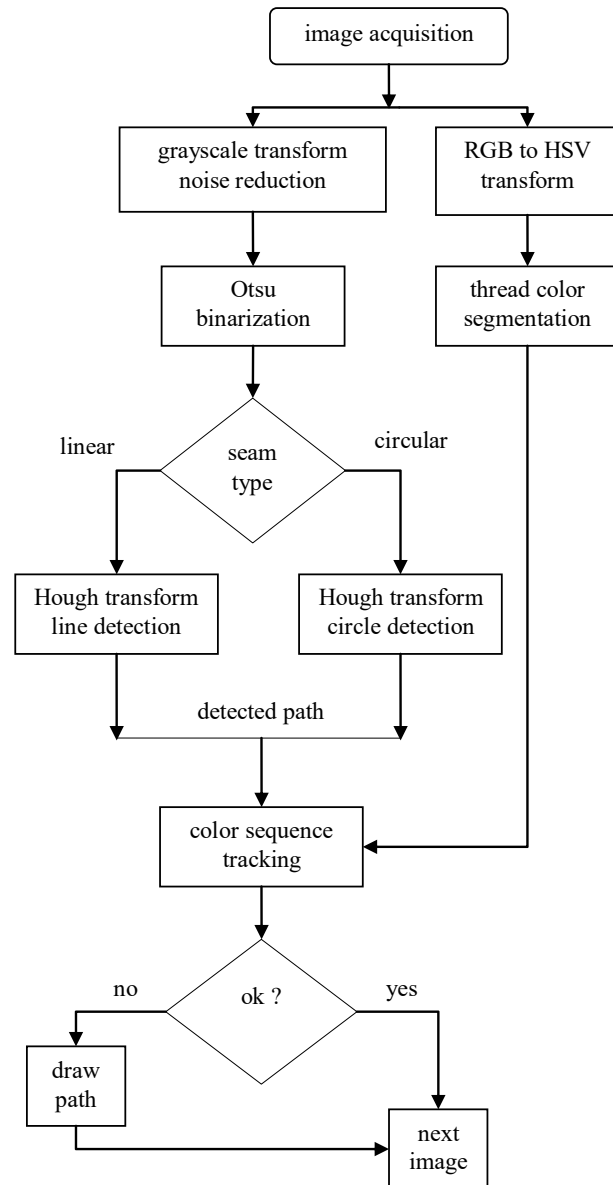
Steps



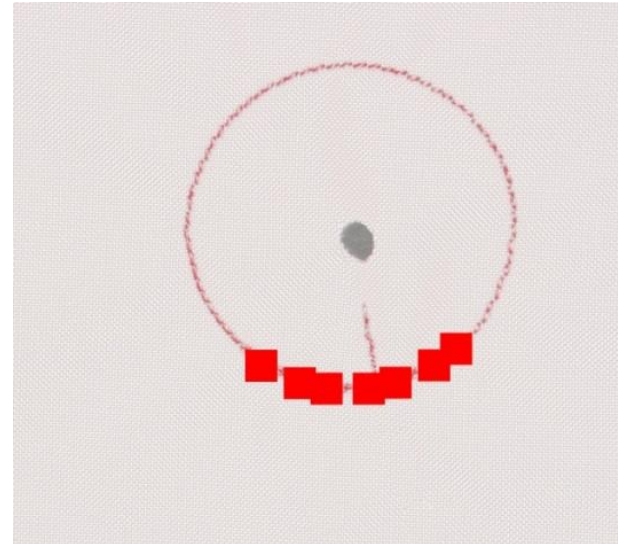
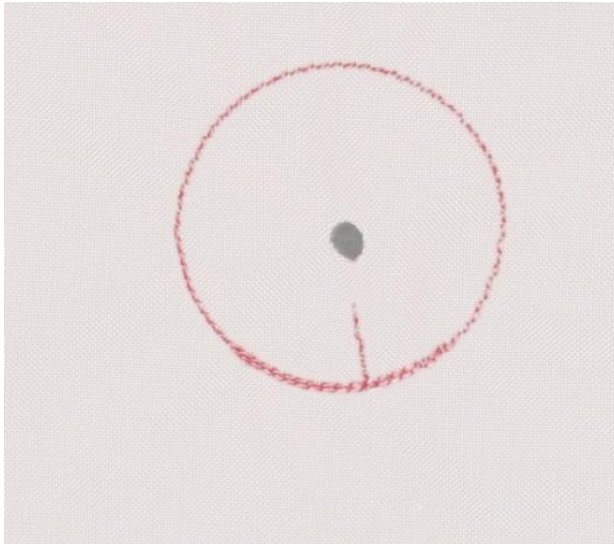
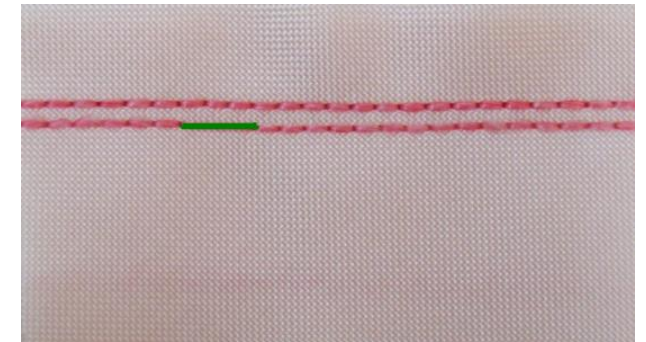
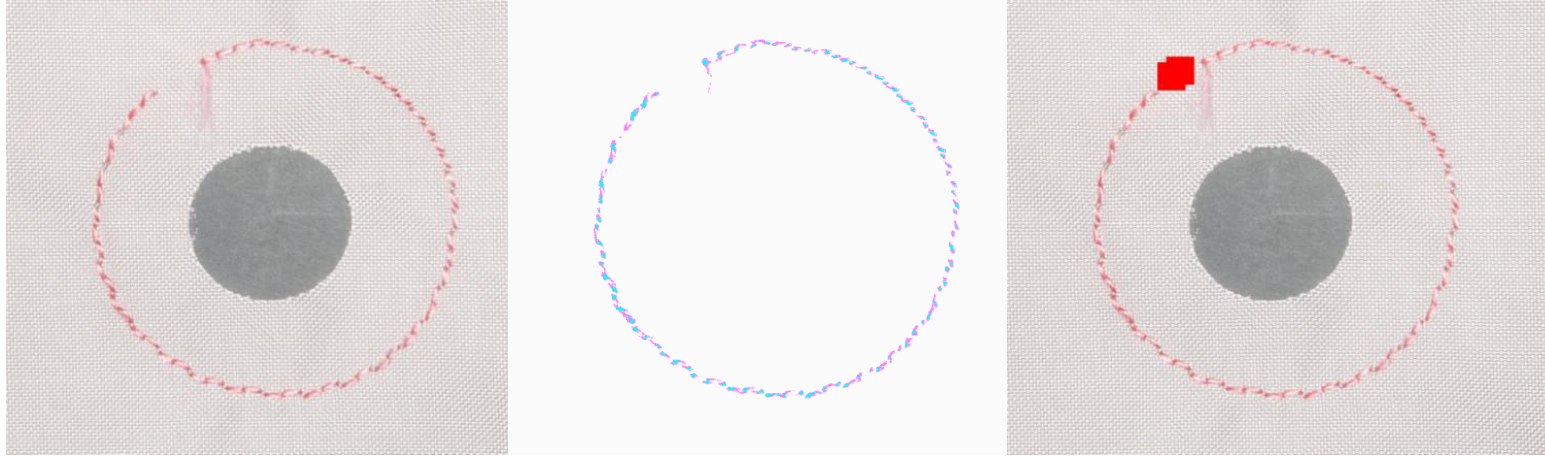
- In view of linear or circular path recognition, the image is converted from color to a grayscale format and smoothed for noise attenuation
- The image binarization was performed using an unsupervised adaptive Otsu algorithm
- The detection of linear seams is made using the Hough transform by assessing the pixels position and their co-linearity
- The detection of circular contour seams was made using the Hough transform for circles, employing an accumulator structure to retain information regarding the detected circle center
- Using morphological information, the algorithm for linear or circular seams control is analyzing the colors being present in the acquired image along with the recognized lines or arcs

IMAGE PROCESSING FOR SEWING DEFECT DETECTION

Steps



Results



Conclusions

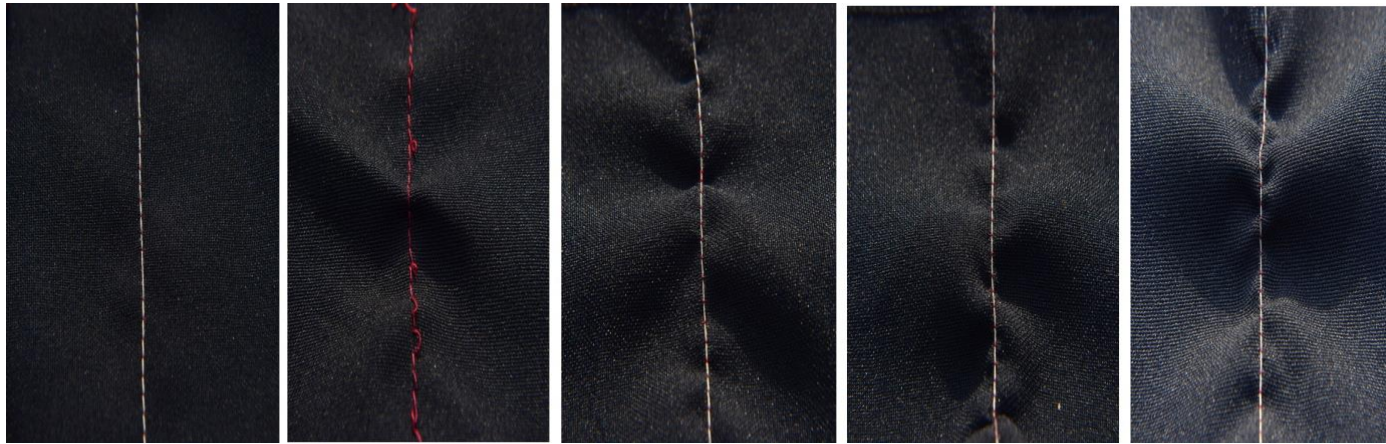


- Besides the properties of fabric, the assembly seams play an important role in airbag functionality
- Due to the fact that the seams cannot be repaired during the production process, any stitching defect will cause a nonconforming product. Intermediate inspection of stitches before the final closure of the airbag is an important stage, since it prevents non-compliant subassembly to pass on the next production step
- Automatic defects detection of seams keeps the sewing process in control and makes the final product comply with the client requirements

Other Computer Vision for Clothing Manufacturing Industry Applications

Other developed systems for textile manufacturing quality control

- Seam puckering evaluation for sewing process



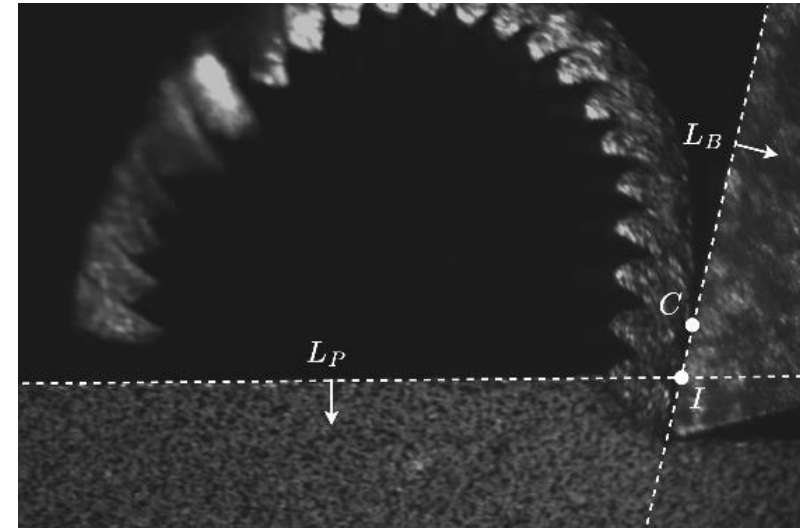
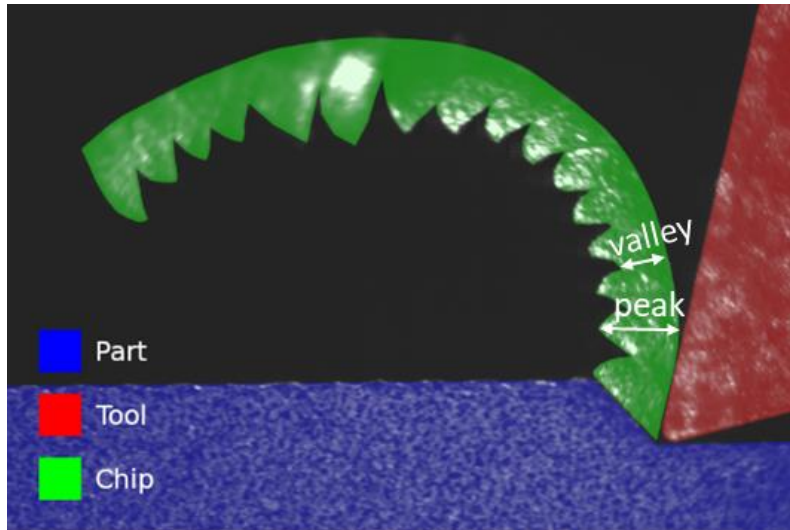
- The assessment of knitted fabric pilling



Automated Chip Measurement Using Image Processing

The Problem

- Numerical simulations of Ti6Al4V machining need validation against experimental chip geometry.
- Serrated chip peaks and valleys are the key geometric features for this comparison.
- Currently measured manually — a tedious, time-consuming process.
- No prior study had automated chip measurements from high-speed video recordings.



The Opportunity

- High-speed video cameras capture chip formation in real time during orthogonal cutting.
- Automated methods generate large datasets quickly without chip preparation for microscopy.
- Prior automated work used optical microscopy images only (Klippel 2022, Carvalho 2023).
- Video-based automation enables denser temporal sampling across full cutting datasets.

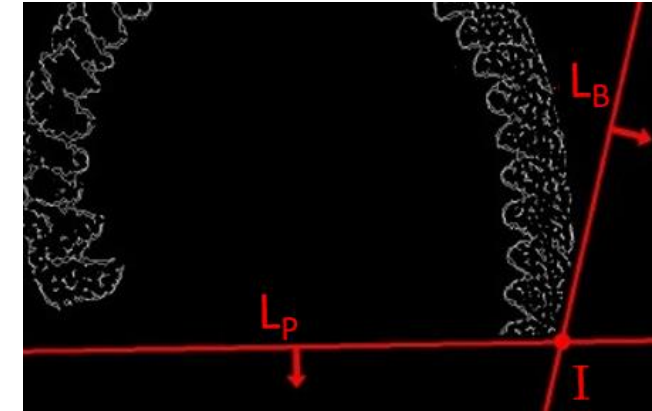
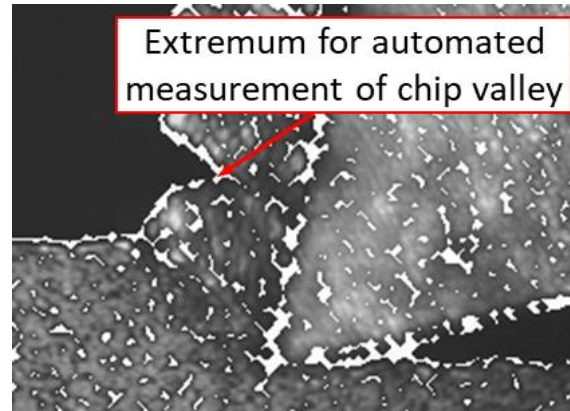
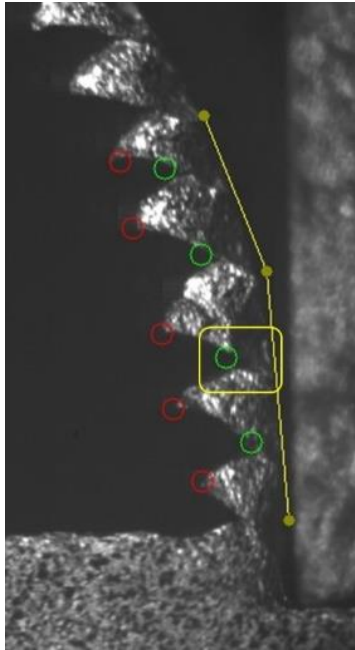
The Target Material

- Ti6Al4V titanium alloy — widely used in aerospace and biomedical applications.
- Known for highly serrated chip formation due to adiabatic shear banding.
- Six cutting conditions: speeds 30, 45, 60 m/min × rake angles 0° and 15°.
- Uncut chip thickness fixed at $h = 0.2$ mm for all experiments.

AUTOMATED CHIP MEASUREMENT USING IMAGE PROCESSING

Key Definitions

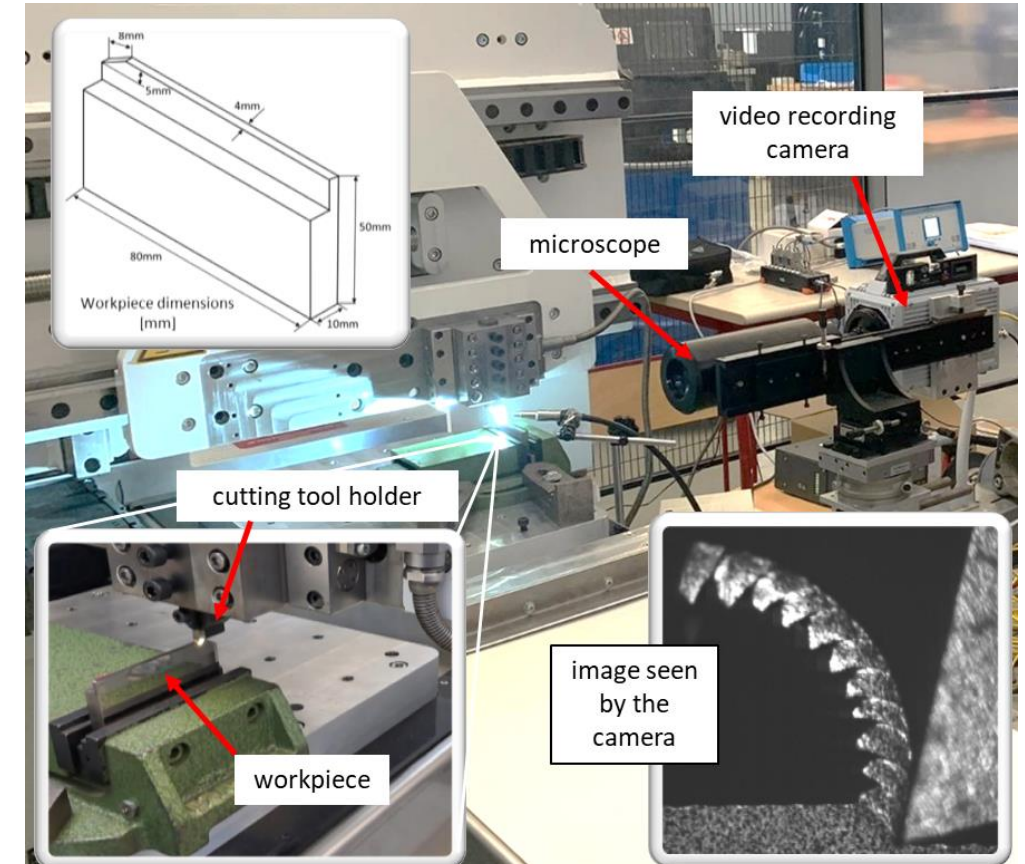
- Peak height (max chip thickness): outer-to-inner distance at a chip segment peak.
- Valley height (min chip thickness): same measurement at the narrowest inter-segment point.
- Measurements made in pixels, scale established from known image resolution.
- Ground truth: manual measurements using Digimizer 6.4.4 image software.



AUTOMATED CHIP MEASUREMENT USING IMAGE PROCESSING

Recording Equipment

- Camera: Photron SA5 high-speed video camera.
- Optics: Questar QM100 long-distance microscope.
- Lighting: Olympus ILP-1 fiber-optic illumination system.
- Resolution: 1024×496 pixels per frame.
- Frame rate: 15,000 fps. Shutter speed: $1/54,000$ s.



Cutting Tool and Workpiece

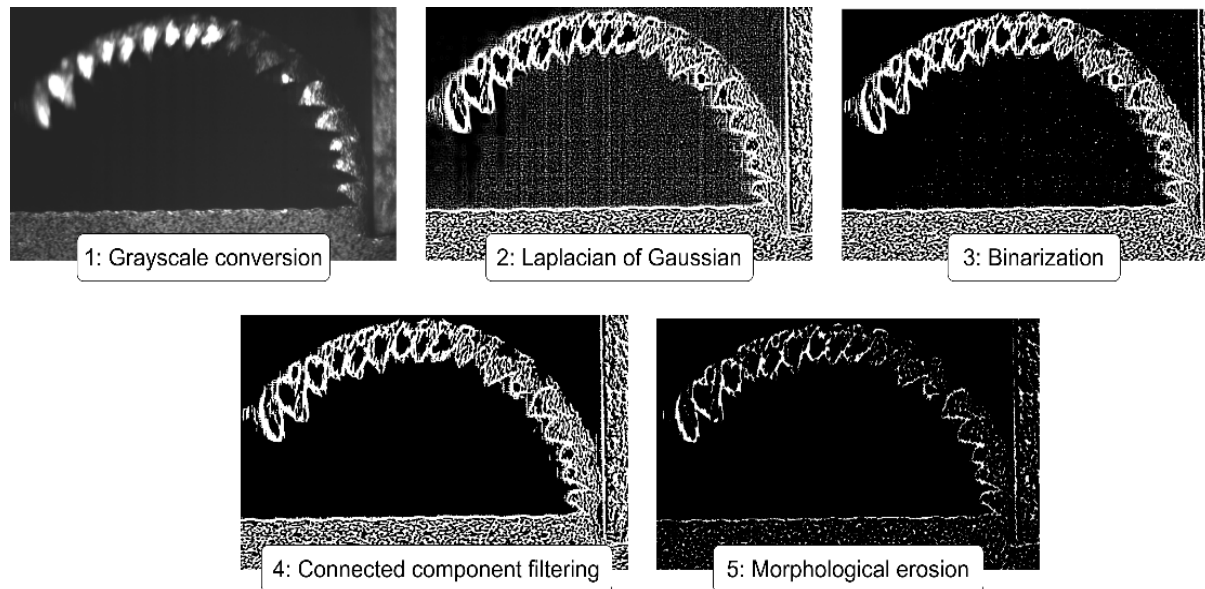
- Tool: uncoated tungsten carbide (CW-6% Co).
- Clearance angle: 7°. Edge radius: $\sim 20\text{ }\mu\text{m}$.
- Workpiece: Ti6Al4V block, $80 \times 50 \times 10\text{ mm}$.
- 8 mm entry chamfer to minimize impact forces.
- Machine table moves at cutting speed V_c ; tool is stationary.

Six Cutting Conditions (100 images each = 600 total)

Dataset	Cutting Speed	Rake Angle	Dataset	Cutting Speed	Rake Angle
1	30 m/min	0°	4	30 m/min	15°
2	45 m/min	0°	5	45 m/min	15°
3	60 m/min	0°	6	60 m/min	15°

Image Processing Pipeline

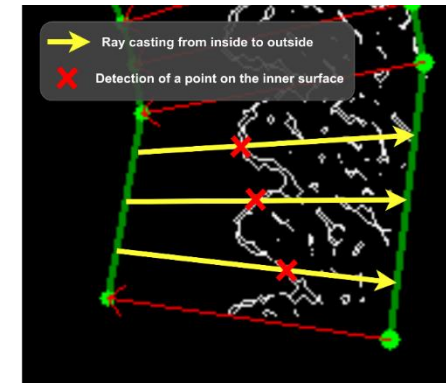
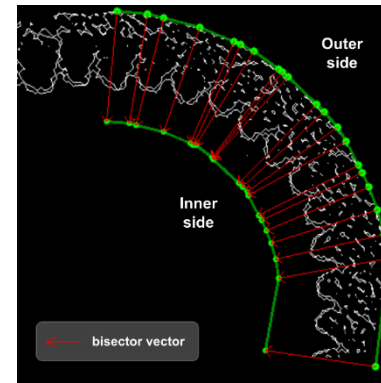
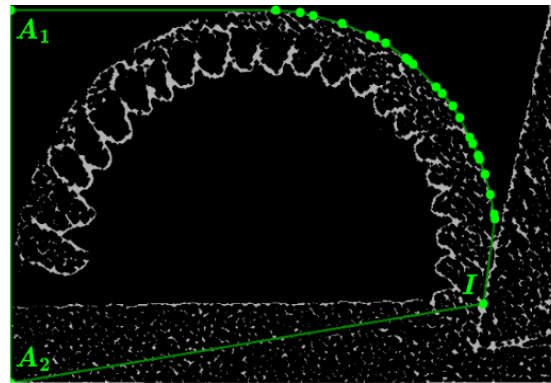
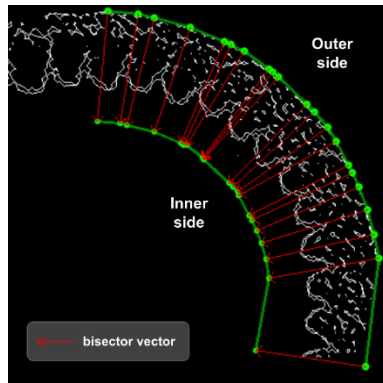
- Step 1 – Pre-processing: RGB → Grayscale → Laplacian of Gaussian ($\sigma=1.4$) → Binarization.
- Step 2 – Artifact removal: Connected component filtering (non-adjacent artifacts) + morphological erosion (adjacent artifacts).
- Step 3 – Chip isolation: Hough transform detects lines LP (part boundary) and LB (tool boundary); white pixels above both lines form the chip point cloud.



AUTOMATED CHIP MEASUREMENT USING IMAGE PROCESSING

Image Processing Pipeline

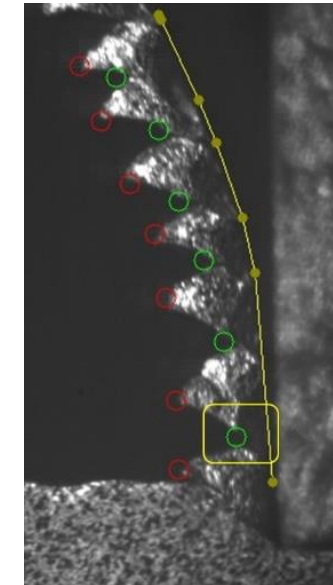
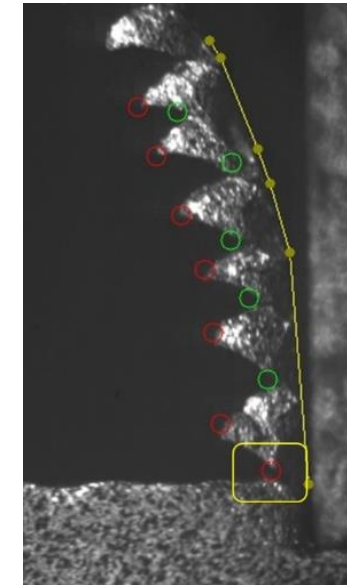
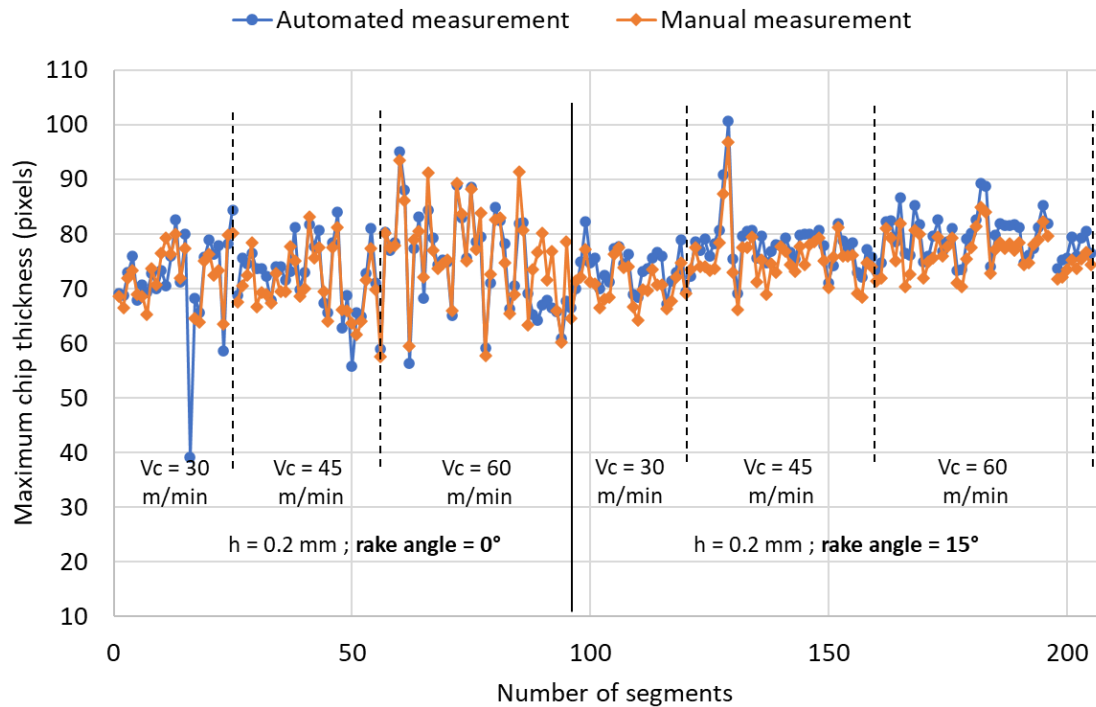
- Step 4 – Outer surface: Convex hull with forced anchor points A1, A2 to handle focal blur on chip edge.
- Step 5 – Inner surface: Translate outer surface inward by $2\times$ uncut chip thickness; ray casting from inner to outer detects surface pixels.
- Step 6 – Cleaning: Outlier detection by neighbor search with radius inversely proportional to proximity to outer surface; linear interpolation replaces outliers.
- Step 7 – Peak/valley detection: Savitzky-Golay filter \rightarrow find_peaks on smoothed thickness signal; quasi-period ω constrains search to $\pm 30\%$.



AUTOMATED CHIP MEASUREMENT USING IMAGE PROCESSING

Results

- Strong agreement across all 6 conditions; algorithm is wrong on only 2 of 207 segments.
- Automated average 77.99 px vs manual 75.53 px — just +3% overestimation.
- Standard deviations nearly identical: automated 5.3 px, manual 5.2 px.



Results

- Automated measurements consistently overestimate valley height by up to 26%.
- Algorithm correctly self-corrects misidentified valleys in subsequent frames.
- Fixable through improved image pre-processing and higher camera acquisition frequency.

$\leq 4\%$

Max deviation
peak height
(all conditions)

$\leq 26\%$

Max deviation
valley height
(pre-proc. bias)

207

Segments
validated vs
manual

1–3%

Gap reduction
with dataset-level
averages

Conclusions

- The textile industry is one of the traditional and dynamic sectors
- The customer quality requirements are constantly changing as a result of trends and the development of production tools
- In order to satisfy clients' demands, the variables that affect product quality must be kept under control during the production cycle: design, manufacturing, delivery and maintenance

Conclusions

- The evaluation process of a product relating to appearance and performance have to rely on a holistic perspective
- Due to long reaction time and fatigue of the human operator, an automatic inspection would be able to verify and classify with a much higher speed and would eliminate the subjective factor

Conclusions

- Computer vision systems can be used both in the pre-production stage, for machines adjustment, and also in product inspection
- The ability to recognize flaws and stop production immediately after the occurrence of the defect is important for manufacturers
- The automatic control system may use different technologies for image acquisition, containing mechanical components, computer software, video cameras, lighting and video equipment

THANK YOU FOR YOUR ATTENTION!

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