

Automatic inspection of percussion cap mass production by means of 3D machine vision and machine learning techniques

A.Tellaache



entidad colaboradora
en igualdad de oportunidades



entre mujeres y hombres

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Introduction

- Exhaustive quality control is fundamental when commercializing critical pieces all over the world.
- Percussion cap mass production, to be mounted in firearm ammunition for sporting use is one of these examples.
- These pieces must achieve a minimum tolerance deviation in their fabrication.
- A machine vision system has been developed for percussion cap mass production total inspection.

Problem Description

- Mass production of percussion caps
- More than a million pieces in 8 hours
- Very critical manufacturing due to their explosive nature.
- Maximum tolerance in their fabrication: $200\mu\text{m}$

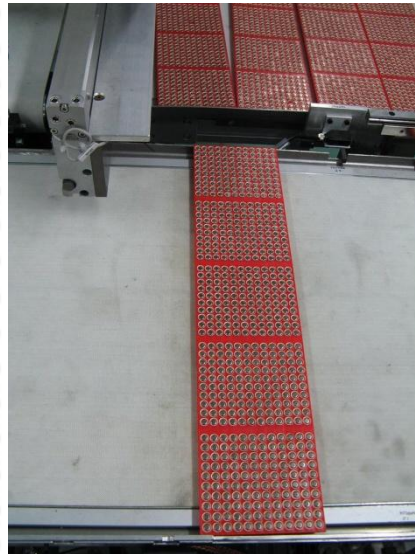


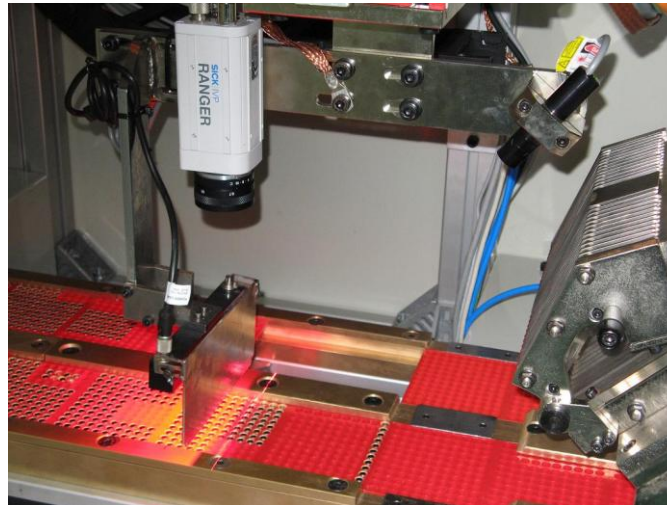
Plate containing 600
percussion caps

Problem Description (II)

- The errors that are suitable to appear in a percussion cap are the following:
 1. Central part of the cap dented
 2. Central capsule badly mounted
 3. Central capsule inverted
 4. Rests of paper in the joints of the cap
 5. No central capsule mounted
 6. Central capsule dirty
 7. External capsule dirty or dented
 8. Percussion cap missing in the plate
 9. Central capsule mounted above tolerance
 10. Central capsule mounted below tolerance

System overview

- Camera Ranger E55 for 2D and 3D image acquisition
- Special lighting system including 3B class line projecting laser for 3D imaging and diffuse red led bar light for 2D imaging.



3D image acquisition

- Image obtained by laser triangulation, composing the image with consecutive 3D profiles

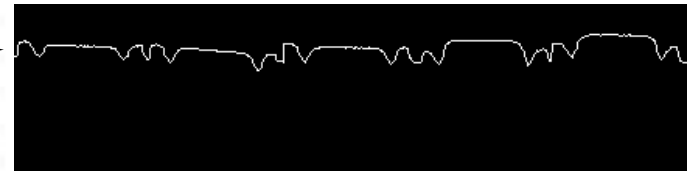
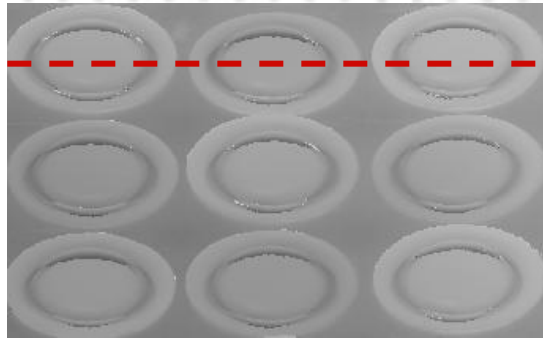
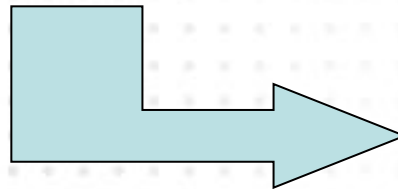
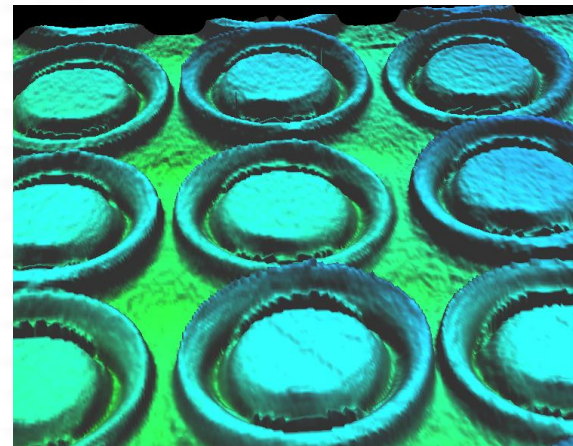


Image composed of line profiles

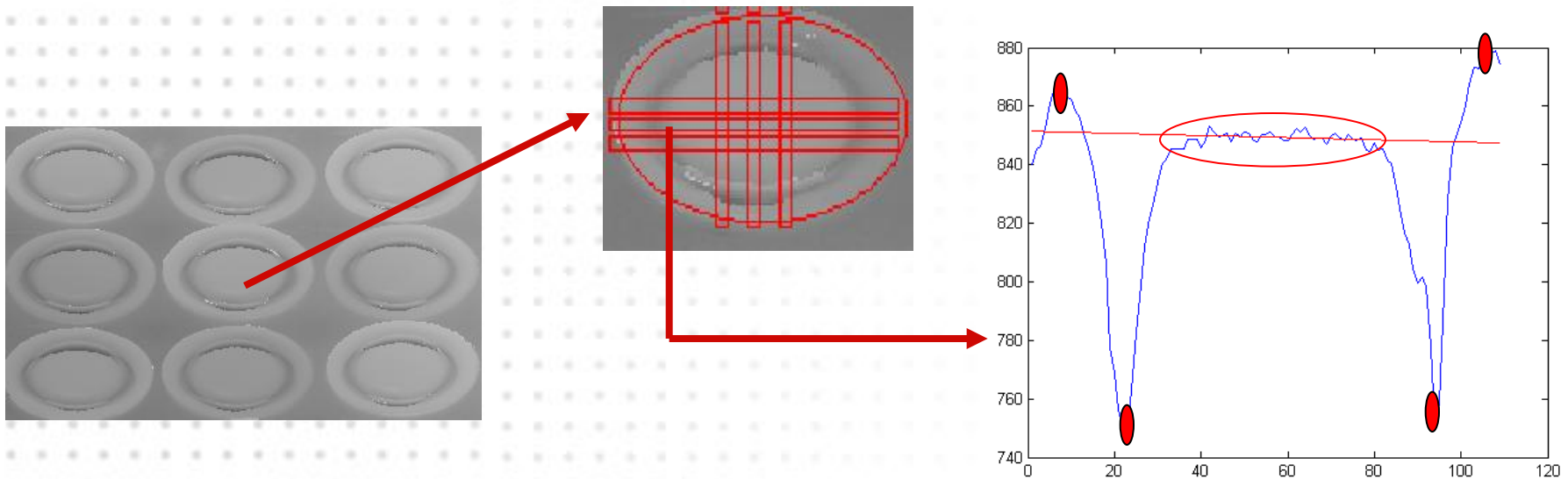


3D interpretation of the image



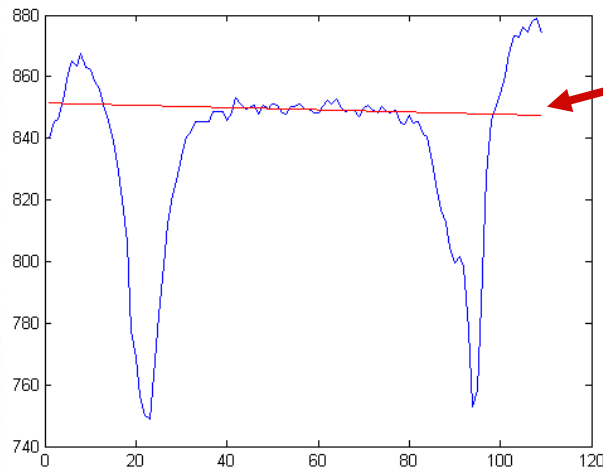
3D image data obtaining

- Six line profiles obtained from each percussion cap.
- Measurements obtained:
 - Maximum and minimum of the beginning of the percussion cap
 - Maximum and minimum of the ending of the percussion cap
 - Mean and Standard Deviation of the central capsule



3D image data obtaining (II)

- For each line profile of the percussion cap, the regression line of the central part of the percussion cap is also calculated



$$y = \bar{y} + \frac{\sigma_{xy}}{\sigma_x^2} (x - \bar{x})$$

Regression line slope: $\frac{\sigma_{xy}}{\sigma_x^2}$

Bias: $-\frac{\sigma_{xy}}{\sigma_x^2} \bar{x} + \bar{y}$

Error:
$$Error = \frac{1}{n} \sum_{j=1}^n \left[y_{r_j} - \left(\frac{\sigma_{xy}}{\sigma_x^2} x_j - \frac{\sigma_{xy}}{\sigma_x^2} \bar{x} + \bar{y} \right) \right]^2$$

These values, along with the measurements obtained, will be used for error detection.

3D image data obtaining (III)

- With all the values extracted from a line profile a data vector is constructed

$$X_i = \{x_1, x_2, \dots, x_{12}\}.$$

x_1 = x coordinate where the maximum at the beginning of the percussion cap occurs.

x_2 = x coordinate where the minimum at the beginning of the percussion cap occurs.

x_3 = x coordinate where the maximum at the ending of the percussion cap occurs.

x_4 = x coordinate where the minimum at the ending of the percussion cap occurs.

x_5 = maximum height value in the central capsule of the percussion cap.

x_6 = minimum height value in the central capsule of the percussion cap.

x_7 = mean of height values in the central capsule of the percussion cap.

x_8 = slope of the regression line

x_9 = bias of the regression line

x_{10} = mean quadratic error between the regression line values and the real values of the central capsule of the percussion cap

x_{11} = difference between the real height value in x_1 and the theoretical value of the regression line at the same point.

x_{12} = difference between the real height value in x_2 and the theoretical value of the regression line at the same point.

Machine learning algorithms for error detection

- Simple Classifiers:
 - Statistical: Bayesian Networks
 - Clustering : 3-NN
 - Decision Trees: C4.5
- Classifier combination: Voting
 - Bayes Network + 3-NN + C4.5

Performance Evaluation

- 1150 line profiles have been used as samples.
- For each line profile a data vector is calculated.
- Each data vector belongs to a class ranging from 1 to 11 (10 errors + class without errors)
- To assess validity 10-fold cross validation method has been applied.
- The validity measures are based on the 4 typical outcomes when classifying a sample:
 - True Positive (TP)
 - True Negative (TN)
 - False Positive (FP)
 - False Negative (FN)

Performance Evaluation (II)

- Taking into account these four outcomes, the validity measures are:
 - Correctly classified instances (CCI)
 - Incorrectly classified instances (ICI): $100\% - \text{CCI}$
 - True Positive Rate (TPR): $TP / (TP + FN)$. Also called Recall
 - False Positive Rate (FPR): $FP / (FP + TN)$
 - Precision (P): $TP / (TP + FP)$
 - F- Measure (FM), defined as:
$$(2 * \text{Precision} * \text{Recall}) / (\text{Precision} + \text{Recall})$$

Performance Evaluation (III)

	CCI	ICI	TPR	FPR	Precision	F-Meas
Bayes Net	87.58%	12.41%	0.876	0.067	0.89	0.882
3-NN	89.49%	10.50%	0.895	0.137	0.874	0.878
C4.5	91.14%	8.85%	0.911	0.086	0.899	0.904
BN+3NN+C4.5	92.27%	7.72%	0.923	0.093	0.911	0.912

- This performance is for each of the six line profiles present in a percussion cap. Taking into account the results obtained in all line profiles, it can be obtained a performance above 95%.

Conclusions

- Work carried out in demand of an industrial final client to inspect potentially problematic pieces.
- Until now quality control carried out inspecting pieces at random and using statistics.
- The system developed constitutes a great advance towards 100% quality inspection of potentially dangerous pieces with a very good performance.

Thank you !!