

# Application of computer vision methods to estimate the coverage of peen formed plates

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## Manufacturing and processing

### ABSTRACT

**Purpose:** this paper aims to present a simple method that allows for a systematic estimation of coverage of peen aluminum workpiece submitted to a peen form process.

**Design/methodology/approach:** This approach is based on the application of computer vision techniques for segmenting amplified images of the shot peening processed surface. The work has employed two combined methods of image segmentation – inductive algorithm generated rule segmentation and a multiagent segmentation system.

**Findings:** The two combined methods of image segmentation has allowed for an estimation of low coverage plates as well as done by human expert. Furthermore a model of the spatial shot distribution was also achieved.

**Research limitations/implications:** The surrogated method is suitable for plates with relative low coverages, circa 50 %.

**Originality/value:** The model can be regarded as useful by accelerating the coverage evaluation in comparison with conventional industrial approach.

**Keywords:** Peen forming; Image segmentation; Inductive algorithms; Multiagent systems

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## 1. Introduction

Shot peen forming is a plastic cold work process of shaping a metallic sheet or panel through the impact of a regulated blast of small round steel shots on its surface, in order to produce a

previously desired curvature. The succession of shots stretches the targeted surface; consequently, a thin compressive residual stress is generated, giving rise to an elastic deformation of the worked surface [1].

Peen forming process planning requires the measurement and control of groups of variables encompassing the shot intrinsic characteristics (diameter and material), the nozzle operation (massic shot flow, translation jet speed and jet angle) and the shot-workpiece interaction (impact velocity, print diameter and exposure time). Traditionally, the effects of all these parameters are considered by monitoring two combined variables – the Almen intensity and the shot coverage [2].

Although the Almen intensity measurement procedure is very well established [3] and interesting solutions have been proposed to estimate this measure from its intrinsic parameters – impact velocity and shot diameter [4], the estimation of shot coverage is still accomplished through the application of lengthy and subjective procedures [5] based on the visual natural human abilities.

The need to measure coverage in a more efficient and reliable way has giving rise to the development of new measurement procedures based on computer vision techniques. Such an approach requires the grabbing of digital images of the peened surface and the application of filtering and segmentation algorithms to the referred images followed by the estimation of the fractions of the areas affected by the shots. Notwithstanding promising, those procedures lack from more robust image segmentation methods since the optical reflective characteristics of the metallic shot surfaces impose extra difficulties to the establishment of suitable threshold values.

Leon [6] proposed a model of the collimated light reflected from polished surfaces, textured surfaces with approximated parallel grooves and spherical surfaces printed by a shot peening process that was applied to construct a robust segmentation algorithm for images of shotted surfaces. However, such a method requires a relatively complex assembly to capture images, since it is necessary to orientate the light source along 32 different angles. Approaching the problem on a different way Handa et al. [7] proposed a much more simple segmentation algorithm, but suitable only for images of perfectly polished surfaces.

In this article, we present two new image segmentation methods applicable to images of aluminum alloy (7050-7451) machined plates shotted by spherical shots exhibiting average diameter of 3.175 mm (1/8"). The proposed methods require a very simple assembly to capture the images and only two orientations for the light source to be used. Considering that the resultant segmented images are post-processed to estimate coverage and that their admitted tolerance should not be greater than 5% [6], two approaches were adopted: one uses an inductive algorithm [8] to generate robust decision making segmentation rules, while the other is based on a multiagent system (MAS) [9], where computer agents, interacting with each other, complement their abilities to solve some of the remaining segmentation problems.

## 2. Materials and methods

### 2.1. Experimental set up

As illustrated in Fig. 1, the images of the workpieces (400 mm×50 mm×5 mm rectangular plates machined from blocks of aluminum alloy 7050-7471) were captured using an optical

microscope Carl Zeiss model Citoval 2 (30x magnification), a collimated 30 W light white source, a CCD RGB video camera Moticam 480 and the image grabbing software Motic Image Plus.

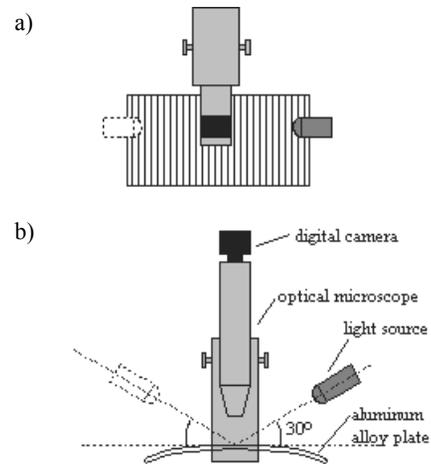


Fig. 1. Image grabbing assembly: a) top view; b) front view

The developed image processing algorithms operate with pairs of images grabbed at two distinct light source illumination angles (Fig. 2).

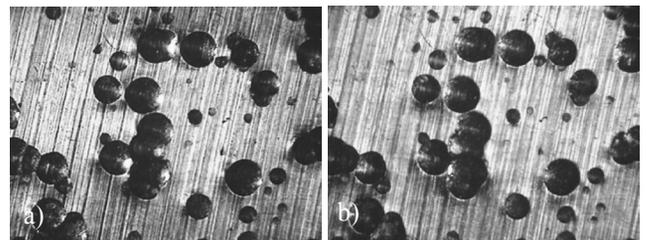


Fig. 2. Images illuminated at: a) 150°; b) 30°

The light source was guided in such a way that the slant angles relatively to the horizontal plane are either 30° or 150° and the intersection of its vertically projected axis is always normal to the plate machining streaks. With such a set up the images present a good contrast between background and the areas of interest (shotted areas). Figure 2a-b shows two such images grabbed using light source orientation angles of 150° and 30° respectively.

### 2.2. Image preprocessing

In the above images, it can be observed that shot printings are characterized by areas where the majority of pixels have low grey levels, except on a small region where there is a high concentration of near white pixels – an effect caused by the reflection of direct illumination over the depressed printed surface. On the other hand, the zones not affected by the shots

(i.e., the background) show a succession of parallel streaks with variable dark to bright grey levels.

It is important to emphasize that using two very distinct light source angles generates images where the reflective areas are situated on different regions of the printings, a necessary condition to apply algorithms that can easily eliminate such undesirable artifacts.

After taking the brightness information from the pair (30°/150°) of grabbed RGB images they were submitted to a filter that eliminates the reflective artifacts by assigning to each pixel  $p(x,y)$  of the output image the minimum intensity value of the corresponding pixels  $p_{30}(x,y)$  and  $p_{150}(x,y)$  of both given input images. Applying such a processing to the images of Fig. 2, we obtain an image (Fig. 3) where the majority of reflective artifacts are eliminated, but as the dark machining streaks are highlighted, the new artifacts that arise can easily be confounded with shot printings.

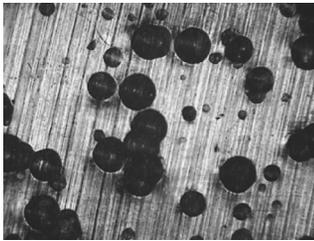


Fig. 3. Output filtered image

The presence of machining streaks texture in the preprocessed images increased the difficulty to obtain satisfactory results through the application of classical image segmentation algorithms. Therefore, after several unsuccessful attempts to identify both spatial and frequency-based filters to attenuate the referred artifacts, two different artificial intelligence techniques – a supervised learning inductive algorithm [8] and a multiagent system [9] – were selected to approach the problem of segmenting images of peen formed plates.

### 2.3. Application of an inductive algorithm

The abilities of acquiring knowledge from examples and representing it in an explicit way are important characteristics of inductive algorithms that make them suitable to approach the focused segmentation problem.

Although there are several types of such class of algorithms, we applied the well known ID3 [10] to a set of image characteristic vectors, in order to induce a decision tree whose traversal generates a set of decision rules to classify image pixels as a ‘printing pixel’ (shot) or a ‘plate pixel’ (‘background’).

The following five local image parameters  $v_i$ , were adopted to build the characteristic vector: mean grey level, variance grey level, median grey level, gradient modulus grey level, gradient angle grey level. Both the mean grey level and the median grey level were chosen because the printings are significantly darker than the background. On the other hand, the non shot areas

exhibit large variations of grey levels and high intensity gradients of equal orientation, characteristics that can be well represented by the last three selected parameters.

It is important to stress that mean, median and variance are local image parameters that depend on the selected convolution window width  $w$ . If  $w$  is less than the machining streak width ( $w_m$ ), the resultant local parameter may confound ‘printing’ and ‘machining streaks’ dark regions. If  $w$  is much larger than  $w_m$ , there is an increase of classification errors near the boundaries of ‘printing’ and background areas.

Induction algorithms require an initial training cycle to teach the inference engine to associate a characteristic vector to its respective class. In the case of ID3, this phase culminates with a decision-tree having paths based on the selection of the highest discriminant parameters, their respective intervals of variation and the associated classes. Each node represents a logical expression comparing the value of a single parameter to an admissible variation interval. Successive nodes are linked to each other up to the final classification node. It is important to emphasize that not all the calculated parameters are necessarily used to construct the decision-tree; the inductive algorithm selects only the relevant ones.

In order to get the best possible decision-tree, the training-set characteristic vectors were based on representative regions of the images. Therefore, the following four distinct types of sub-images were selected: ‘dark printing area’, ‘printing with a few remaining reflective area’, ‘bright non-shotted plate area’, ‘non-shotted plate area with shadows and dark machining streaks’.

Two possible groups of rectangular areas of interest are shown in Fig. 4.

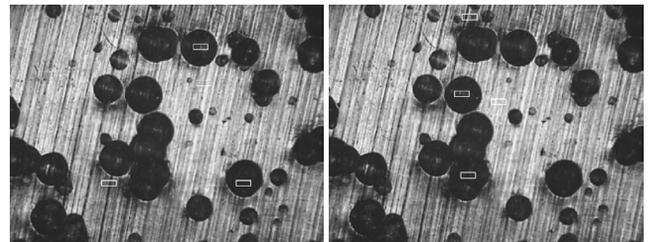


Fig. 4. Representative areas of the images

Considering that each area corresponds to a 50x20 sub-image, a training-set based on  $n$  such examples would have a total of  $1000n$  characteristic vectors.

Using the ID3 algorithm, the following sequence of tasks was implemented to properly segment the images:

- Selection of interest areas.
- Evaluation of the local properties  $v_i$ ,  $i=1,\dots,5$  of the areas referred above.
- Organization of the training-set: pairwisely each group of ordered  $\{v_i\}$  properties to its respective  $c_i$  classification;
- Training the ID3 algorithm with the training-set obtained in step 3.
- Construction of a segmentation algorithm based on the decision rules induced by the ID3.
- Applying the induced algorithm to segment new preprocessed images.

All the image processing algorithms required to implement the above procedure were developed in the C++ language. Concerning the ID3 algorithm used in this project, we selected one of the machining learning tools embedded in the public domain open source software MLC++ [10].

## 2.4. Application of a multiagent system

'Agents' are computer entities that perceive the environment in which they are immersed in and act upon it in order to achieve their own design objectives, either by simply responding to changes or by planning to obtain the best possible result with all information available. Therefore, those entities are reactive and rational: they react to changes meanwhile proactively seek to reach individual goals. When intentionally aggregated in computational solutions called MAS, agents can compete or cooperate to complement individual abilities, self-coordinate the use of resources and have a broader view of a partially observable environment, in order to collectively solve problems whose informational complexity is due to physical or logical distribution or volume of data to process [9].

The development of a MAS is mainly based on two tasks [12]: defining the scope of the problem and designing the roles of the agents involved in the solution. The intention on using a MAS to address the coverage problem is to refine the results obtained with well known image processing and computer vision techniques. Thus, the input for the projected MAS is not a monochromatic image, but instead a binary image resulting from the application of a previous method like the ID3-based method presented before (Fig. 5).

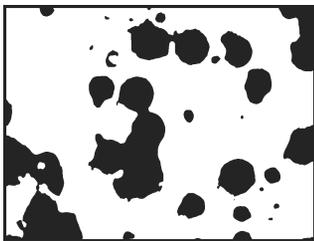


Fig. 5. Input binary image to be refined by the MAS

In this new image the coverage problem now relies on correcting the remaining errors in the regions (dark pixels) produced by the prints, which are either caused by flaws (missing pixels) or shadows (exceeding pixels). The prints are expected to be circular and this tendency can be verified in most of the edges, thus the first agent role designed is of a 'Center Identifier' (CI), whose design objective is to identify a print by locating its center in the image and by calculating its radius in pixels.

The best way to control the number of CI agents created turned out to be the Voronoi vertices [13] calculated from positions taken from the edges of the regions themselves. Since the most circular a print is the closer the vertices are to each other, an instance of a CI agent is created at the position of each vertex in a way that they can interact to decide collectively which vertex best describes the print center.

The image itself is part of the environment of the CI agents, and their interactions are based on the perceptions of the edge marks (the same ones used to calculate the Voronoi vertices) and the other CI agents positioned nearby (Fig. 6). Based on the edge marks an agent (A) can infer what should be the radius ( $r$ ) of the print whose center it may be representing. It can also infer the direction (opposed to the edge) where it should look for another CI agent (B) that might be better positioned to represent the same print. Any CI agent can only perceive other agents that are positioned inside its radius area (B and C).

After discarding the agents that are not positioned towards the opposed direction of the edge, the agent A compares its radius with the neighbor agents' radii and then communicates to all agents whose radii are smaller than they can give up because it is better positioned. This interaction happens among all existing CI agents that can spot each other, so the ones that do not receive any communication shall end up inferring that they are indeed well positioned to represent a valid print.

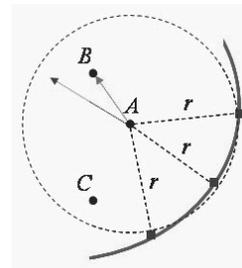


Fig. 6. A, B and C are Voronoi vertices associated to edge markers. A CI associated to vertex A concludes that its circle of radius  $r$  is 'valid' after observing and interacting with the CI's associated to B and C

The concurrent execution of agents is an intrinsic characteristic of any MAS, and to avoid having false positives due to the premature elimination of an agent that would eliminate another one if it had a chance, it was necessary to design a new role called 'Region Analyzer' (RA). An instance of a RA agent is created per detached region in the image and it is responsible not only for calculating the Voronoi vertices, but specially for managing the conclusions of all CI agents in its region in a way that their self-elimination are only allowed once the analysis reaches an equilibrium (i.e. no more messages are exchanged among the CI agents). Finally, another role designed was of 'Segmentation Manager' (SM), which has only one instance and it is responsible for managing the creation of the RA agents per region and to communicate with the user through the system's graphical interface.

The image segmentation MAS was developed using the Java language and the open source tools Jade [14] and Jadex [15]. Jade provided the means to build the agents and to implement their communication mechanism according to the Foundation of Intelligent Physical Agents (FIPA) standards [16]. Jadex, on the other hand, was used to build the reasoning mechanism of the agents, based on the architecture of Believes, Desires and Intentions [17], from which the observations of one given agent are described and handled as 'believes' which are used to activate or inhibit objectives and plans of action written in Java.

### 3. Experimental results

In the following two sections we present the peen forming coverage estimates obtained through the application of both the image segmentation methods briefly exposed before.

#### 3.1. Results from the ID3-based method

In order to evaluate the performance of the ID3 induced segmentation rules, a well segmented reference image of a shot peened plate was manually generated using the natural human ability to identify objects of interest (shot printings) in the scene. As illustrated by the Fig. 7, this reference image corresponds to a calculated coverage of 26.1%.

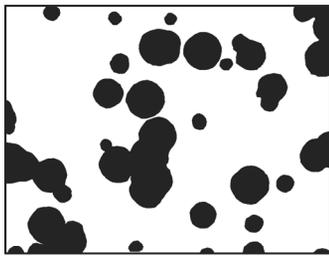


Fig. 7. Reference manually segmented image

On the reference image, training-set pixels were extracted from sub-images corresponding to the ones illustrated in Figure 4. After testing different window sizes to calculate the image local parameters, 11x11 windows were adopted, since in such case ID3 induced a decision tree (Fig. 8) that is well-fitted to the data.

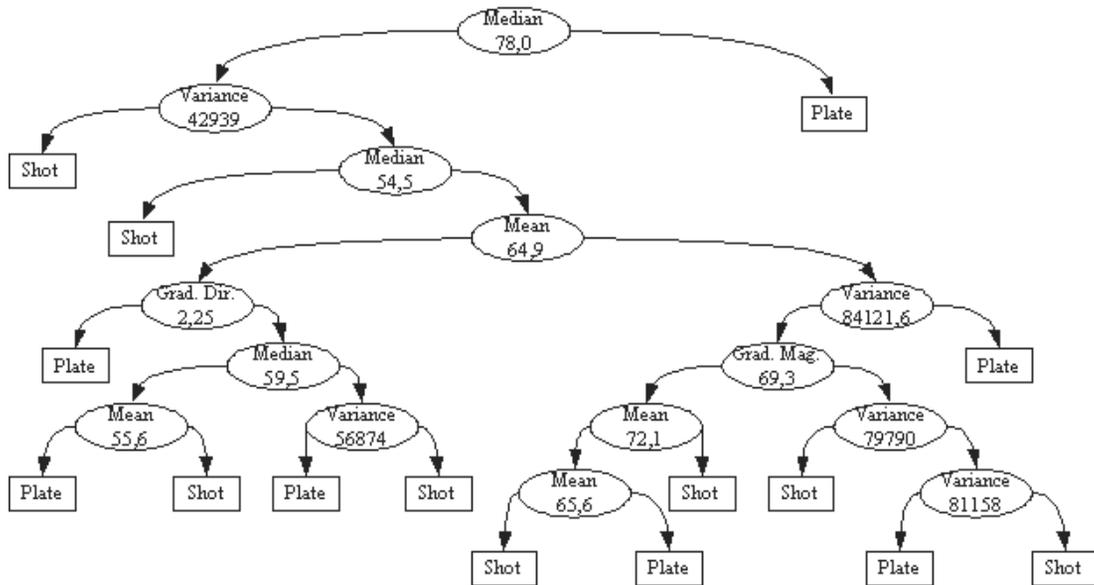


Fig. 8. Decision tree and associated segmentation rule induced by the ID3 using training-sets of Fig. 4a and an 11x11 window

Therefore, applying the correspondent induced segmentation rules to all the pixels of the preprocessed image of Fig. 4 we get a segmented image (Fig. 9). The comparison of this image with the reference image of Fig. 7 exposes some discrepancies that are the result of generalization errors induced by the segmentation rules.

As shown in Fig. 9, the majority of misclassification errors concentrate around the printing boundaries, exposing the inability of the selected parameters to identify pixels that belong to those transition zones. However, much more significant are the misclassification errors (1) and (2) corresponding, respectively, to pixels from reflective printing regions classified as *plate* pixels and pixels from dark machining streaks classified as *printing* pixels.

Using the second group of regions from Fig. 4b to generate the training-set, similar results were obtained. In Table 1, the classification performance of the induced algorithm is estimated for two distinct training-sets and three different window sizes.

Table 1. Coverage estimation versus misclassification errors

Window size		11×11	15×15	21×21
Training-set from Fig. 4a	Coverage	28.3%	28.2%	25.7%
	Error (1)	3.4%	3.0%	2.1%
	Error (2)	1.2%	0.9%	2.5%
Training-set from Fig. 4b	Coverage	26.1%	25.9%	23.1%
	Error (1)	1.9%	1.5%	1.1%
	Error (2)	1.9%	1.7%	4.1%

In Table 1, it is remarkable the coherence of the results, even when different image examples and window sizes are used to generate the training-sets. Practically, all the estimated coverage values are within the 5% stipulated variation interval around the reference coverage of 26.1%.

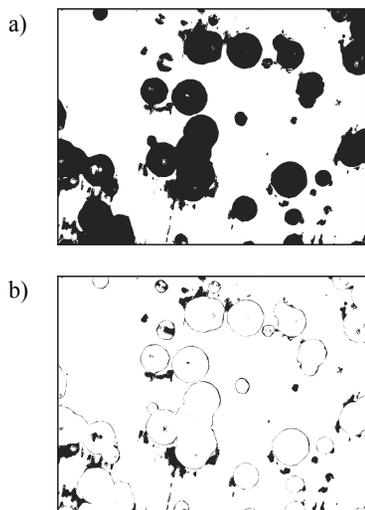


Fig. 9. (a) Segmented image; (b) Corresponding errors for the examples of Fig. 4a using an 11x11 window

### 3.2. Results from the MAS based method

After setting up some expert-knowledge parameter values associated to the CI agent evaluation behavior, like the minimum and maximum acceptable diameters of a valid printing circular region and the expected ratio of shot overlapping, the developed image segmentation MAS was applied to refine the results of a segmented image (see Fig. 5) previously generated by the ID3 induced segmentation rules.

As illustrated in Fig. 10, although clear improvements can be identified in the quality of the segmented image, misclassification errors still remain. Moreover, a straight comparison between images 9a and 10 shows that: 1) the use of a minimum acceptable radius permit to correct the errors caused by reflections, as indicated by 'a', but, at the same time, favors the confusion of shadowed zones with shotted areas, as indicated by 'b'; 2) the adopted parameters enhance agents 'visual accuracy', giving them the ability to identify superimposed shotted areas, as indicated by 'c', but this ability fails when the shotted area is positioned at the image boundaries, as indicated by 'd'; 3) yet, the segmentation process carried on by the agents is not completely harmed by the presence of incomplete interest objects adjacent to the image boundaries, as again indicated by 'd'; 5) since the circular zones are completely defined by their center coordinates and respective radii, the segmented image delivered by the MAS can be considered as a simplified model of the spatial distribution of shots generated by the peen forming process.

In Table 2, the estimates of the plate peen forming coverage supplied by the ID3 induced segmentation rules and by the refinement produced by the MAS are finally compared with the reference value, supplied by traditional human visual inspection. As it can be noticed, the favorable effect on the accuracy results due to the application of the MAS, recommends its use as a refinement tool to improve the quality of the image segmentation process.

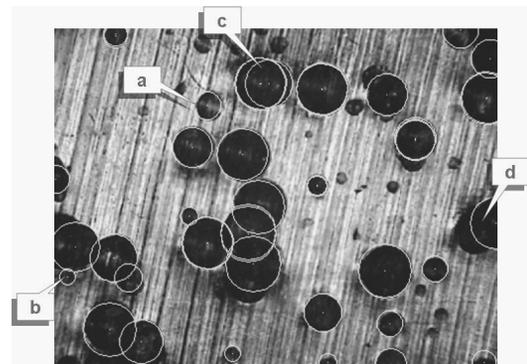


Fig. 10. Segmented image refined by the MAS

Table 2.  
Coverage estimates comparison

	Segmentation performed by an expert	Segmentation based on the ID3 induced rules	Segmentation refined by the MAS
Estimated coverage	26.1%	27.7%	25.4%
Relative error	---	1.6%	-0.7%

## 4. Conclusions

The estimation of shot coverage, a fundamental parameter to control peen forming processes, is usually performed by very lengthy and subjective techniques dependent on the natural visual abilities of human beings. New solutions, based on a computer vision approach, have been proposed in order to overcome the inherent difficulties imposed by the traditional technique, but they either require relatively complex setting up for image grabbing or are not well suited to deal with texturized surfaces.

In this article, we demonstrate that the combination of segmentation rules generated by an inductive algorithm and the refinement of a specialized multiagent system can closely emulate the actions of human beings concerning their ability to discriminate shotted from non-shotted areas of plates submitted to low coverage peen forming processes.

By using the ID3 algorithm to induce decision rules to segment preprocessed images of texturized shot peened workpieces, it was possible to obtain a robust segmentation algorithm able to accurately identify shot printing areas and estimate coverage within 5% tolerance around the reference value. Giving this segmented image to a properly designed multiagent system to refine, a further improvement in the previously estimated coverage can be achieved; even more, a simplified model of the spatial shot distribution generated by the peen forming process can be finally synthesized.

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