COMPUTER VISION METHOD TO ESTIMATE THE COVERAGE OF AN ALUMINUM ALLOY PLATE SUBMITTED TO PEEN FORMING PROCESS

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Abstract. *Considering that the coverage is one of the most important parameters to be evaluated in order to implement a controlled peen forming process, it is proposed a robust computer vision algorithm to measure relatively low level coverages in shot peened alluminum alloy plates. After applying to the shot peened surface images a sequence of common smoothing filters, the referred algorithm calculates a set of characteristic image parameters that is used to teach an induction algorithm to recognize shotted regions. The application of the resultant induced rule to the preprocessed images generates segmented images where the estimation of shot coverage can be made within a 5% tolerance around the reference value.*

Keywords*: peen forming, shot peening, computer vision, machine learning*

1. INTRODUCTION

The peen forming conformation process planning requires the measurement and control of several parameters encompassing shot intrinsic characteristics (diameter and material), nozzle operation (massic shot flow, translation jet speed and jet angle) and shot-workpiece interation (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 (Burakowski e Nakonieczny, 1981).

Although the procedure to measure Almen intensity is very well established (Clarke e Birley, 1981) and interesting solutions have been proposed to estimate this variable from its intrinsic parameters like impact velocity, shot diameter and exposure time (Haulbold *et al*, 2005), the measurement of shot coverage is still accomplished through the use of lengthy and subjective procedures based on the visual natural human abilities (SAE, 2003).

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 percentages (necessarily less than 100%) of the areas really affected by the shots. Notwithstanding promissing, those procedures lack from more robust image segmentation methods, since the optical reflective characteristics of the metalic shotted surfaces impose extra difficulties to the establishment of suitable threshold values.

Leon (2001) 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. On the other hand, Handa *et al* (2005) proposed a much more simple segmentation algorithm, but suitable only for images of polished surfaces.

In this article, it is presented a new image segmentation method applicable to images of alluminum alloy (7050-7451) machined plates shotted by spherical shots of 3,175mm (1/8") diameter. The proposed method requires 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 posprocessed to estimate coverage and that its admitted tolerance should not be greater than 5% (Leon, 2001), an approach based on induction algorithms was adopted to generate robust decision making thresholding rules.

2. MATERIALS AND METHODS

The proposed computer vision method to measure slow coverages (less than 100%) of shot peening workpieces requires the accomplishment of four tasks:

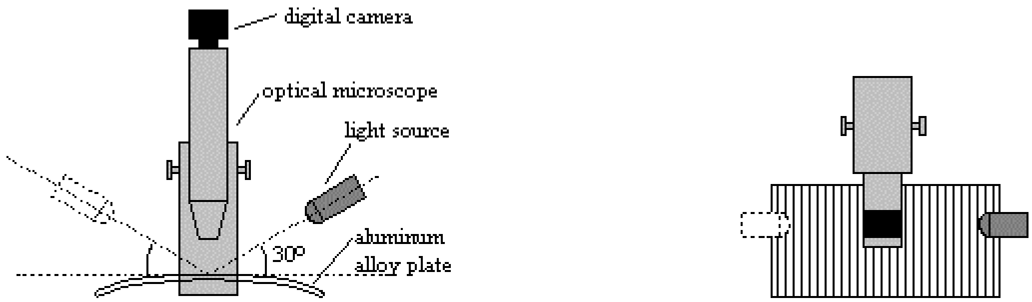
1. Image grabbing: It is necessary to grab two images of the workpiece using two different orientations for the light source;
2. Image initial processing: The grabbed images are preprocessed and fused into a unique smoothed image.
3. Image segmentation: An induction algorithm is trained to recognize shotted regions giving rise to a robust segmentation rule.

4. Coverage estimation: The previously induced rule is applied to segment the preprocessed image and the (shotted area)/(total area) ratio is finally calculated.

2.1 Image grabbing

The assembly to grab the images includes:
- optical microscope Carl Zeiss model Citoval 2 (30x magnification);
- collimated 30 W light white source;
- CCD color video camera Moticam model 480;
- image grabbing software Motic Image Plus.

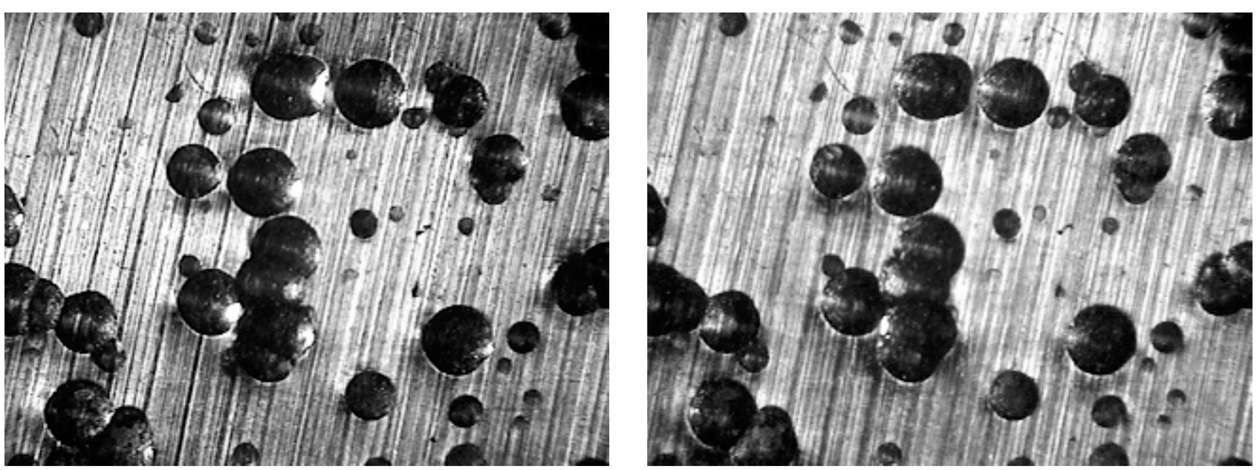
As it is illustrated in the Fig. 1, two images of the shotted surface are grabbed, each one correspondent to a different light source illumination angle.



(a) (b)

Figure 1. Front view (a) and top view (b) of the image grabbing assembly.

The light source is orientated 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 allways normal to the machining streaks. With such a set up the grabbed images present a good contrast between background and the areas of interest (shotted areas). Fig. 2a-b shows two such images grabbed using light source orientation angles of 150° and 30° respectively.



(a) (b)

Figure 2. Grabbed images using two different source light orientation angles: (a) 30° ; (b) 150°.

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

Using two very distint light source orientations gives rise to images where the reflective areas are situated on very different regions of the printings, a necessary condition to apply algorithms that can elliminate such undesirable artifacts.

2.2 Image PreProcessing

The pair (30°/150° illuminated) grabbed RGB images are firstly converted to monochromatic ones, since color information is unimportant to the proposed segmentation method. Next, these images are submitted to a fusion information algorithm that elliminates the reflective original artifacts by simply assigning to each pixel P(x,y) of the output image the minimum intensity value of the correponding pixels $P_{30}(x,y)$ and $P_{150}(x,y)$ of both given input images. Applying such a processing to the images a-b of Fig. 2, results the output image of Fig. 3, where it can be observed that the majority of reflective areas have been elliminated; however, an undesirable effect is also produced: the dark machining streaks have been highlighted, giving rise to artifacts that the segmentation algorithm can easily confound with the shot printings.

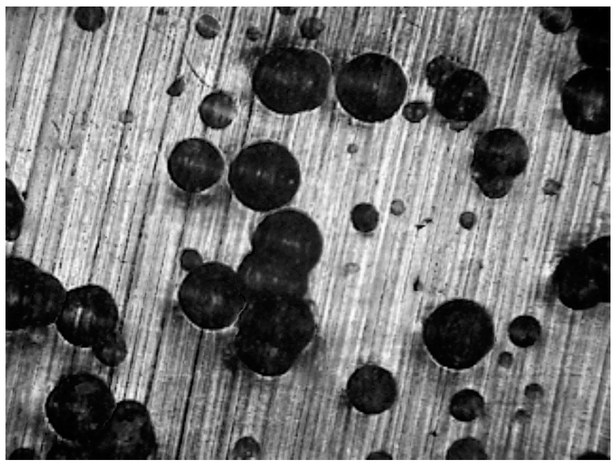


Figure 3. Fusion of the images of Figures 2a-b

2.3 Image Segmentation

The presence of texturized machining streaks in the preprocessed images makes extremely difficult to obtain satisfactory results through the application of classical segmentation algorithms. After several unsuccessful attempts to identify spatial or freqüency-based filters to attenuate the referred artifacts, it was concluded that the solution of such a segmentation problem would require the aid of artificial intelligence techniques.

The ability of acquiring knowledge from examples and representing such knowledge in a explicit way is an important characteristic of inductive algorithms that makes such class of intelligent tools natural candidates to solve the proposed segmentation problem. ID3 (Quinlan, 1986), in particular, has been chosen since it is relatively easy to find public domain implementations of such an algorithm.

After applying ID3 to a set of characteristic vectors, a decision tree is generated. Traversing such a tree, along its successive nodes and branchs, results a set of decision rules to make classifications based on the characteristic vector components. For the considered segmentation problem, a vector of the following five characteristic local image parameters has been proposed:

- mean grey level;
- variance grey level;
- median grey level;
- gradient modulus grey level;
- gradient angle grey level;

Two possible classifications are considered:

- *printing* pixel (associated to a shotted area)
- *plate* pixel (associated to a non affected area)

The selection of adequate parameters to compound the characteristic vector is of paramount importance in order to produce a reliable decision-tree. Both the mean grey level and median grey level have been chosen because the printings are significantly darker than the background. On the other hand, the non shotted areas show large local variations of grey level as well as high intensity gradients of approximately equal orientation, visual characteristics that can be well represented by the last three selected parameters.

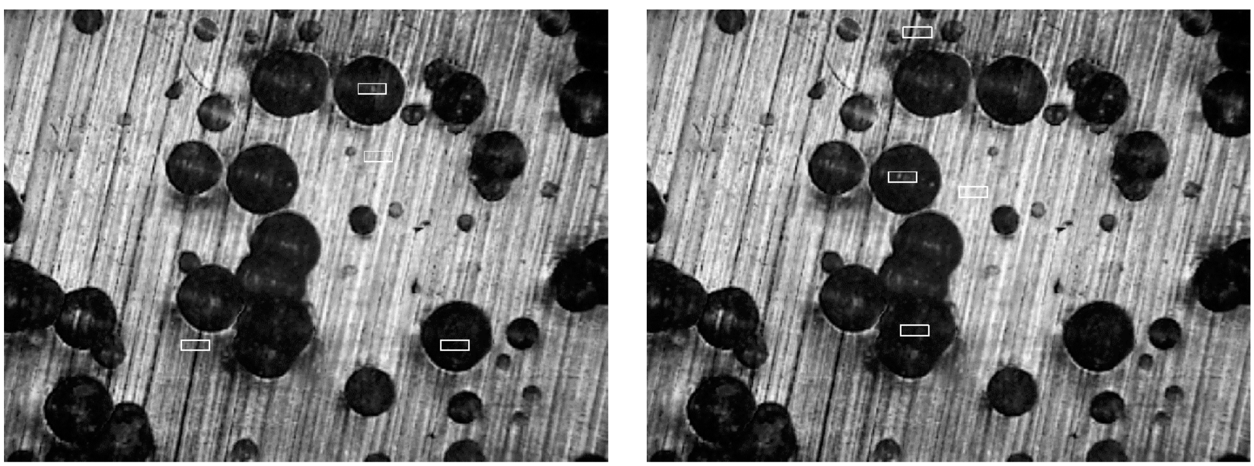
It is important to stress that mean, median and variance are local image parameters that depend on the selected convolution window size. If it is less than the expected width of the machining streaks, the resultant local parameters have not the ability to discriminate the dark regions from both printing and machining streaks areas. On the other hand, if a large window is selected, the parameters loose their ability to represent a local image characteristic, giving rise to an increase of classification errors near the boundaries of printing and background areas. Consequently, is advisable to adopt windows with size a little greater than the machining streaks width.

As all the methods based on supervisioned machining learning, induction algorithms require an initial training cycle necessary to teach their inference engine to associate the characteristic vectors (training set) with their corresponding classifications. In the case of ID3, this phase ends with a decision-tree relating the best discriminant parameters, their respective intervals of variation and the associated classes. Each node of this tree represents a logical expression comparing the value of a single parameter to an admissible variation interval. Successive nodes are linked to each other until a final node, representing a classification, is achieved. It is important to emphasize that not all the calculated parameters are necessarily embedded in the decision-tree nodes; the induction algorithm selects only the real relevant ones.

In order to get the best decision-tree possible from ID3, the characteristic vectors of the training set have been based on regions that represent the majority of image examples. As a consequence, four distinct types of sub-images have been selected to extract the vectors of the training set:

- 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 four areas of interest are shown in the Fig. 4. Considering that each example corresponds to a rectangular (50x20 pixels) sub-image of 1000 pixels, each training set based on these examples would have a total of 4000 characteristic vectors..



(a) (b)

Figure 4. Possible sets of representative pixels of typical shot peened workpíece images

Using the ID3 algorithm, the following sequence of tasks have been been implemented in order to obtain proper segmented shot peened workpiece images:

1. Selection of a set of interest areas containing representative pixels of the preprocessed images;
2. Evaluation of the local properties associated to the selected interest areas;
3. Construction of the training set by associating each group of ordered properties calculated in step 2 with a proper classification;
4. Training the ID3 algorithm with the training set obtained in step 3.
5. Construction of a segmentation algorithm based on the decision rules induced by the ID3;
6. Applying the induced segmentation algorithm to segment new preprocessed shot peened workpiece images.

It is important to emphasize that all the image processing and analysing algorithms necessary to implement the above mentioned procedure have been developed in C++ and integrated to the so called *SIVCOMP* platform, an image processing environment of the Instituto de Pesquisas Tecnológicas do Estado de São Paulo (Martins, 2007) that aims to facilitate the development of computer vision algorithms. The ID3 algorithm used in this project is one of the machining learning tools embedded in the public domain open source software MLC++ (Kohavi *et al*, 1996).

2.4 Coverage estimation

After segmenting the images, the estimation of shot coverage is easily accomplished: pixels classified as belonging to a printing region are counted and the total number of such pixels (*Nprint*) is divided by the image area (*A*), i.e.:

$$Coverage \approx Nprint/A. \tag{1}$$

3. EXPERIMENTAL RESULTS

In order to evaluate the performance of the ID3 induced segmentation rules, a well segmented reference image of a shot peened workpiece (Fig. 3) has been manually generated (see Fig. 5), using the natural human ability to identify objects of interest (shot printings) in the scene. This reference image corresponds to a calculated shot coverage of 26,1%.

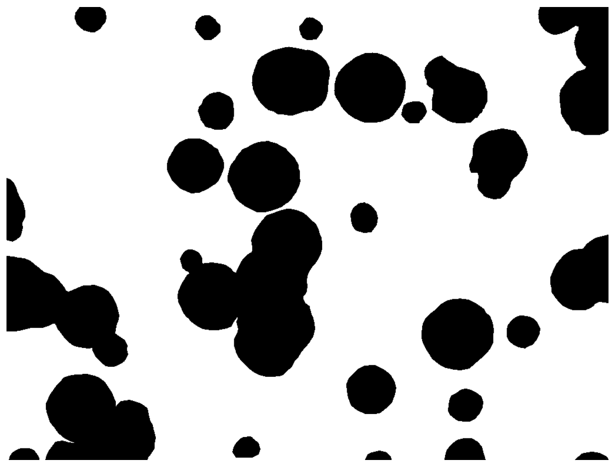


Figure 5. Reference image segmented with the use of human expertise

On the reference image, pixels for the training set have been extracted from sub-images corresponding to the ones illustrated in Fig. 4. Considering that the machining streaks width is approximately 10 pixels wide, four different window sizes have been adopted to calculate the local parameters (mean, variance and median) associated to those selected pixels:

- 7 x 7 pixels
- 11 x 11 pixels
- 15 x 15 pixels
- 21 x 21 pixels

Characteristic vectors derived from the 7x7 window give rise to a decision-tree with more than 100 nodes. Huge trees like this usually indicate the occurrence of over fitting, a behaviour that prevents the induced decision making rule to be generalized to other examples than the ones used during the training.

Much better results are obtained when the training set is based on the characteristic vectors derived from the 11x11 window – approximately the value of the machining streaks width. With the pixels sets of the Fig. 4a, ID3 induces the decision-tree of Fig. 6, where it can be noticed that the first and more discriminant parameter is the local median: if less than 76,0 decision process follows the left branch; otherwise, the right branch. Applying the corresponding segmentation induced rule to all the pixels of the preprocessed image of Fig. 4 results the segmented image of Fig. 7. Comparison between this image and the reference image shows some discrepancies that are the result of generalization errors induced by the segmentation rule.

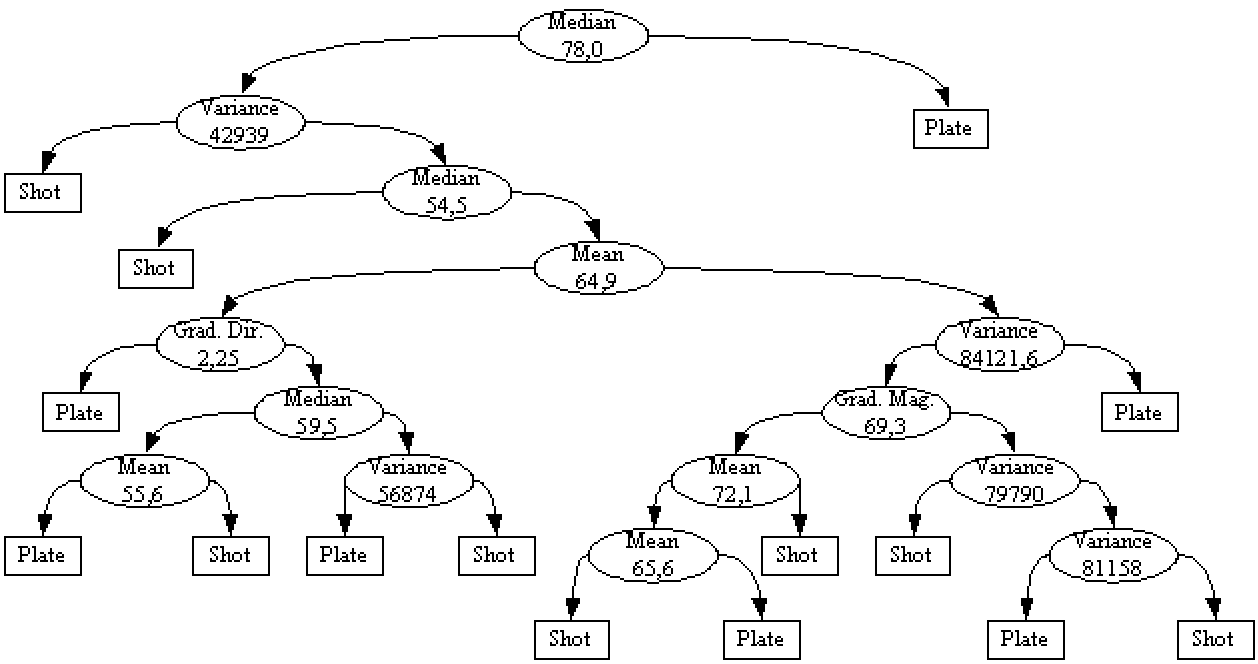
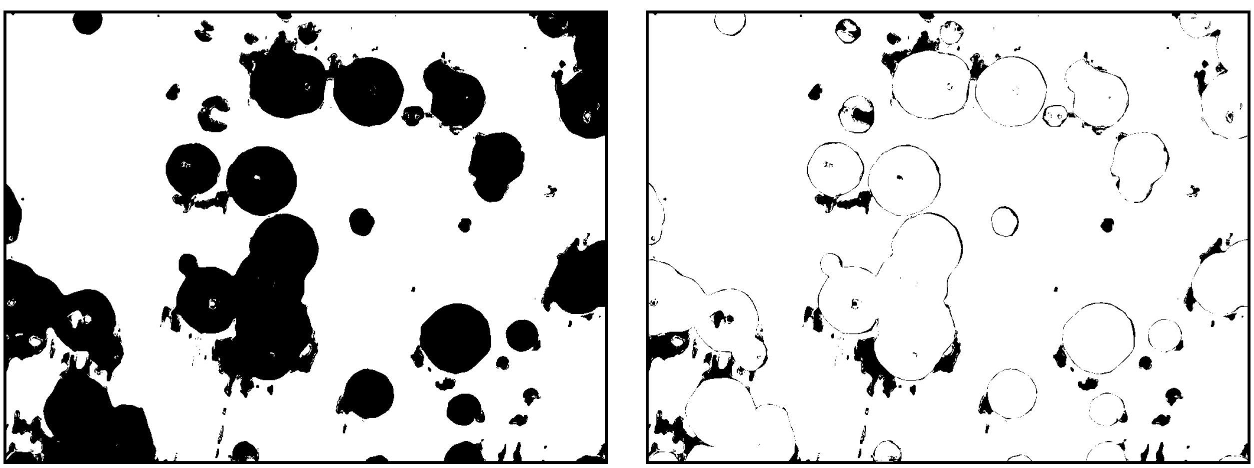


Figure 6. Decision tree and associated segmentation rule induced by the ID3 applied to the training sets of Fig.4a using a 11x11window

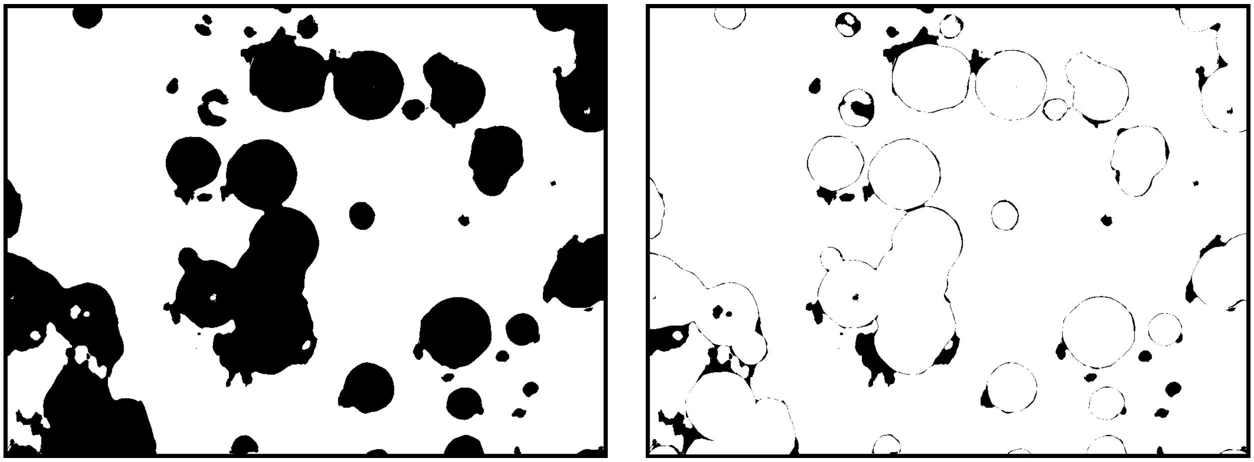


(a) (b)

Figure 7. Segmented image (a) and corresponding errors (b) for the examples of Fig. 4a using 11x11window

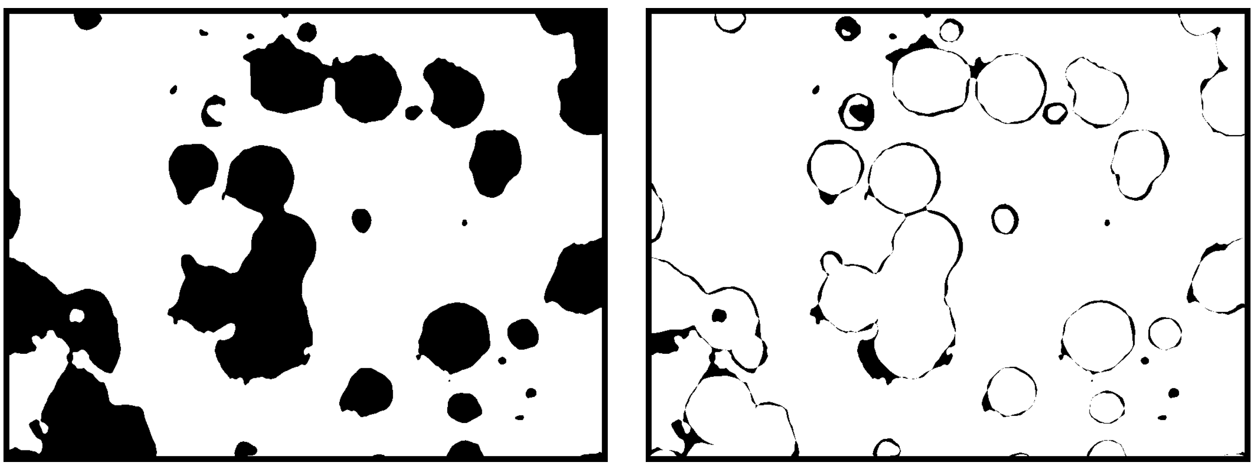
It can be noticed in the images above that some misclassification errors concentrate around the printing boundaries, which results from the inability of the selected parameters to identify the pixels that belong to those transition zones. Some attempts have been made to include an extra class - *boundary* pixel – in the induction process, but the inherent difficulty to visually classify those pixels during the training phase gave rise to inconsistent data and, as a consequence, to bad induced segmentation rules. However, it must be emphasized that much more significant are the two following misclassification errors: pixels from reflective printing regions being classified as *plate* pixels and pixels from dark machining streaks areas being classified as *printing* pixels.

The segmented images obtained from the same training set based on pixels extracted from the Fig. 4a using 15x15 and 21x21 windows can be observed in Figs. 8-9.



(a) (b)

Figure 8. Segmented image (a) and misclassification errors (b) for the training set based on pixels extracted from the Fig. 4a using a 15x15 window



(a) (b)

Figure 9. Segmented image (a) and misclassification errors (b) for the training set based on pixels extracted from the Fig. 4a using a 21x21 window.

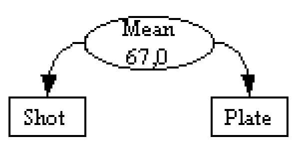


Figure 10. Decision tree induced by the algorithm ID3 using the training set based on pixels extracted from the Fig.4a using a 21x21 window.

Decision trees as well as the resultant segmented images derived from both the characteristic vectors based on the application of 11x11 and 15x15 windows are similar. However, it is important to notice that the use of the 21x21 window gives rise to a very simplified decision tree (Fig. 10), with a single node and two branches, where the only parameter considered to discriminate *plate* and *printing* pixels is the mean grey level. This under fitted decision tree sinthesizes a very generalized segmentation knowledge that, when applied to the test images is unable to correctly classify the pixels that should otherwise be identified by their intrinsic local properties that are not considered by the induced rule. As a consequence, misclassification around the boundaries increase in the images segmented by this extremely generalized rule.

Using the second group of regions of Fig.4b to generate the training set, similar results are obtained. In Tab. 1, it is shown the calculated performance for each induced algorithm.

Table 1. Experimental results for coverage estimation and the corresponding misclassification errors (reference coverage = 26,1%)

		Window size		
		11x11	15x15	21x21
Training set based on examples of the Fig. 4a	Coverage	28,3%	28,2%	25,7%
	Error 1[(1)]	3,4%	3,0%	2,1%
	Error 2[(2)]	1,2%	0,9%	2,5%
Training set based on examples of the Fig. 4b	Coverage	26,1%	25,9%	23,1%
	Error 1[(1)]	1,9%	1,5%	1,1%
	Error 2[(2)]	1,9%	1,7%	4,1%

(1) : pixels belonging to dark machining streaks classified as printing pixels
(2) : pixels belonging to reflective printing zones classified as plate pixels

Analyzing Tab. 1, it is remarkable the coherence of the achievable results, even when different image examples and window sizes have been used to derive the training sets. Practically, all the coverage estimated values obtained are within the 5% stipulated variation interval around the reference coverage of 26.1%. On the other hand, it can be noticed the favorable effect of the only two classes classification problem on the attenuation of the difference between the automatic estimated values and the reference one. The observed discrepancy on the estimated coverage values is a consequence of the differences between the two types of classification errors.

4. CONCLUSIONS

The estimation of shot coverage, a fundamental parameter to control shot and peen forming processes, is usually performed by very lengthy and subjective techniques dependent on the human visual ability. New solutions, based on a computer vision approach, have been proposed to overcome the inherent difficulties imposed by the traditional technique, but they either require relatively complex set up for image grabbing or have a limited scope for dealing with textured surfaces. In this article, a new induced based computer vision technique proposes to solve the coverage estimation problem using only two images of shot peened machined workpieces that present parallel streaks textured surfaces.

Using the ID3 algorithm to induce decision rules to segment preprocessed images of textured shot peened workpieces, it could be obtained a very robust segmentation algorithm that was able to identify the shot printing areas in such a way that coverage was estimated within 5% tolerance around the reference value.

In order to generate the characteristic vectors used to teach ID3 discriminate *printing* (shotted) areas from *plate* (non affected) areas, significant image regions (dark printing areas, printing reflexive areas, bright plate areas, shadowed plate areas and dark machining streaks areas) as well as visually discriminative local parameters (mean grey level, variance grey level, median grey level, gradient modulus grey level and gradient angle grey level) have been selected *a priori*. Only little variations in the estimated coverage value have been observed when the segmentation rule is induced from training sets derived from two distinct sets of image significant regions. However, the window size, used to calculate the image local parameters, demonstrated to exert significant influence on the discriminative ability of the induced tree: the best results have been obtained when the windows size is a little greater than the machining streaks width.

Because the segmentation problem comprehend only two classes of objects – *printing* or *plate* – the coverage measurement error is proportional to the difference between the false positive (*plate* classified as *printing*) and false negative (*printing* classified as *plate*) classification errors. Although relatively small, the use of new, different local image parameters to compose the characteristic vectors, could eventually lead to shorten those errors, giving rise to more robust induced segmentation algorithms.

5. ACKNOWLEDGEMENTS

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