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Quality Analysis Measurement for laser cutting

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Abstract ***- A new approach to automated quality measurement of laser cut in industrial metal cutting processes is presented. The paper demonstrates how is possible to exploit the link between the shape of the erupted sparks from the metallic piece and the final quality of the edges of the laser cut, and propose a solution to automate the quality measurement. The analysis of the shape of the sparks is performed by using images from a camera during real time functioning. The trade-off between accuracy and robustness versus complexity was considered in order to achieve a prototype solution working in real time.***
Keywords - Laser Cutting, Neural Networks, Quality Analysis, Feature Extraction, Image processing.

1. Introduction

All over the word automated laser cutting is having an exponential growth and diffusion in the sheetmetal and material processing [1]. Early detection of defects in metal manufacturing industries and measurement of the process quality are becoming one of the key issues regarding the important economic impact over the industrial process.
Presently, the quality inspection of the laser cuts is performed by offline inspections of the edges of the metal by practiced operators. In the literature, different approaches are presented. In [2], correlation between the values of two sensor of different spectral sensitivity (to observe the process, and to compute the temperature of the process) and the cut quality is studied. Sharpness measurement of cutting edge by using scattered laser diode light is proposed for cutting tools in [3]. The aim of the study is to measure the radius of the cutting edges (degree of wear) of the cutting tool positioned in a known position.
This paper describes how to exploit on-line measures to automatically achieve quality detection in laser metal cutting. Within the activities performed in the EU SLAPS project, Trumpf GmbH observed that important information about the cut quality can be derived by studying the shape of the jet of sparks below the cutting kerf. Trumpf provided experimental data and human-made classifications for our research. The sparks are created by hot rejected matter, expelled from the metal during the cut. A suitable pumped gas is used to reduce oxidation of the metal and to help the expulsion of the melted metal from the cutting area. The pumped gas helps the formation of the sparks jet. A camera is placed to capture the shape of the jet generated during the cut process (fig.1).

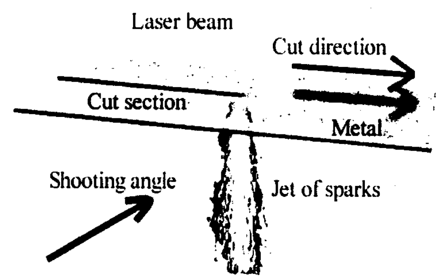


Figure 1: Camera position

Trumpf analyzed qualitatively a great number of jets: this research pointed out that the shape of the sparks' jet can be linked to the quality of the cut edges. The appropriate metal edges should be perfectly squared and continuous, without any residual material remaining in the edges area. A metal piece -with the described characteristics- presents better resistance properties, and subsequent welding is facilitated since no subsequent edge cleaning and refining is required. Although laser-cutting technique are commonly utilized in manufacturing industries, presently they are far from be perfectly optimized. Typical defects detectable in laser cat pieces are shown in fig.2. The edges can be not perfectly squared, discontinuous, or have small pearls (not perfectly expulsed metal attached near the edges, typically called *pearls of burrs*, or simply *burrs*). These kinds of cuts are considered *"rejectables"*. Our analysis showed that all the described defects of the laser cutting are strongly correlated with the shape of the spark jet. Fig.2 shows how the shape of the jet changes in different cutting conditions.
The automatic quality classification system can be achieved by defining suitable indexes of the shape of the jet. The indexes must be automatically processed starting from the input images, and can be used as inputs to a final classifier. Five indexes permit a good high-level description of the sparks shape respect to the detection of cutting defects (fig. 2, bottom). The first is a Boolean value, indicating the presence of the jet in the image (**Pjet**). The second is Boolean value indicative of presence of the burrs (**Pburr**). The last three indexes describe:

- the inclination of the spark jet (**α**). It is strongly related to the speed of cutting with respect to thickness of the metal.

- The wideness of the "nucleus" of the spark jet (β). It is related to the phenomenon called *Excessive Drag*. In this case the final edges are not perfectly squared.
- The whole opening angle of the jet (γ). Strong difference between the γ and β angles can reveal abnormal situation in the sparks jet, for example *divided jets* (typical in discontinuous cuts).

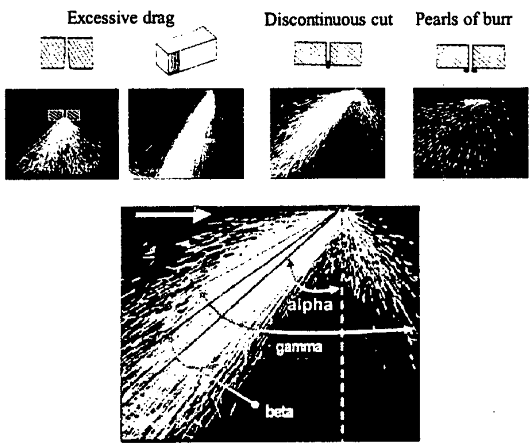


Figure 2: Defects and indexes definition

The angles in fig.2 are drawn by a human operator, since there are no exact definitions of what is the "nucleus" or the "whole opening angle of the jet". Our goal is to measure the angles that correctly mimic the choices of the human operator. The optimum definition of indexes is the one that optimizes the behavior of the quality final classifier.

The final classifier can exploit additional information coming from the field: the state of the cut system (i.e. cut speed, type and thickness of metal, laser type etc.). The cuts are classified in three classes: *acceptable*, *not acceptable* and *not classifiable*. The latter class is necessary since particular shapes of the sparks jet are ambiguous. Often the corresponding cut metal pieces have an intermediate quality. The dubious cuts can be evaluated by traditional direct edges inspection. This is reasonable since the corresponding percentage is very low (less than about 15%). An optimal classifier should minimize the frequency of both of classification errors and dubious cuts.

2. The classification system

In this paragraph, we describe the architecture and implementation of the quality analysis system for laser cutting, from a high-level point of view. We also describe the results achieved with real images. The automatic quality system can be summarized as in fig.3.

The images sequence, coming from the camera, is extracted and synchronized with the state information of the cut system (block 1, fig. 3). The indexes of each image are processed, and they are sent to the S*ingle Image Classifier* (block 3, fig. 3).

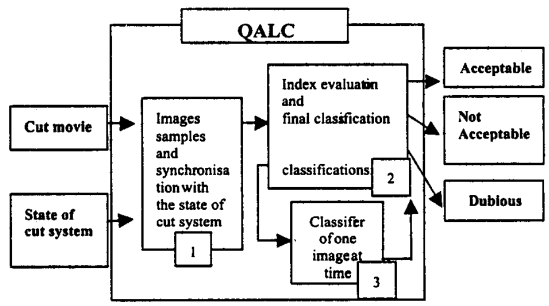
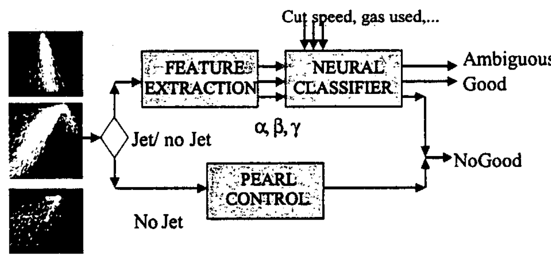


Figure 3: Architecture of the QALC system



Composite System

Figure 4: Single image classifier

The *Complete Sequence Classifier* (block 2, fig.3) processes the results of single-image-classification. Presently, this classifier implements the "worst case" rule: if one image is evaluated not acceptable, the complete cut will be not acceptable. Different rules can be adopted giving different weights to the different single image classes.

The S*ingle Image Classifier* can be seen as the core of the final system. The critical problem to be faced in this module is the strong variability of the shape of the sparks jets (fig.2). The S*ingle Image Classifier* (fig.3) can be considered as a *composite system* that suitably combines the capabilities of the neural networks to tackle the variability of the input images and effectiveness of standard methods in calculating the angles [4]. Since the jet shape can vary widely in shape and intensity, and is not possible to state a precise definition of the "jet presence condition", the module to evaluate the jet presence (fig.4) is implemented using a neural network. An accurate selection of the example images inserted in the *training set* (the set used to tune neural network parameters during the training phase) allows obtaining good discrimination between the two classes. Furthermore, a neural network presents the considerable advantage of being intrinsically parallelizable. Similarly, there are no rules that can efficiently distinguish between small metal pearls and isolated sparks as a result of their similarity. For this reason the *Pearl Control* module was also implemented using a neural network.

The *Feature Extraction* module aims to measure the α, β and γ angles. The input images of this module surely contain a "standard" sparks jet, due to the previous neural classification. Our approach focuses the processing on each row of the image, finding where, in each row, the intensity pattern shows spark typical increment and decrement (the left and right border of the spark). From the two sets of points, a linear regression can identify the left and right lines delimiting the β angle (fig.2). The angle α can be calculated by considering the bisector line of the β angle. Using different prefiltering for the input image (different threshold binarization [5]), the same algorithm described for the feature extraction can match the "nucleus" angles (when the normalized intensity threshold is higher than 95%) or the overall jet angle γ (when the threshold is lower than 30%).

The results of the linear regression can be considerable enhanced if the vertex position of the jet is known. The identification can be done by using two subsequent feed forward neural networks [6]. The sub-sampled image is input to a first net (*net1*), witch searches patterns similar to the vertex of the jet (the image is 64x64 pixel, and the input matrix for *net1* is 8x8 pixel). The area that is candidate to contain the vertex is marked. A second net (*net2*) works only on the marked zone to identify the vertex coordinates with higher precision.

The use of two neural networks (selection of area of interest, and refining) permitted the reduction of 93% of calculation time with respect to a full scan of the same image with *net2* only. Moreover, the application of *net2* over a complete image of jet is not advisable because some sparks at the extremity of jet are similar to a shape of vertex, and can be recognized by the *net2* as the vertex (fig. 5).

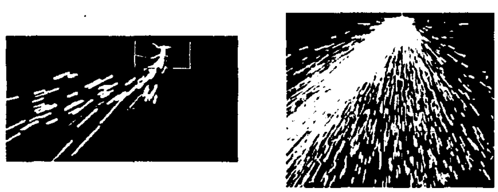


Figure 5: The left image highlights a thin vertex. In the mage on the right, isolated spark are very similar to the previous thin vertex.

The α, β, γ angles final and the cut system status (metal thickness, cutting speed, gas used and pressure, etc.) are input to the final neural classifier, witch recognizes the cut as *acceptable*, *not acceptable* and *not classifiable*. This neural network has a limited complexity since only two hidden neurons are required to achieve appropriate classification accuracy.

The real time constrains directly impact on maximum computational complexity. Different neural networks can ensure reasonable accuracy but with different computational complexity (depending on the number of input, hidden neurons, etc.). An approach based on multicriteria analysis [7, 8] -a technique used in decision support systems- allows for evaluating the cross validation results (for example differently weighting the mean error, its standard deviation, their maximum value) versus the computational complexity of the composite system (for example number of flops, latency). As an example, the weigh criteria utilized for our evaluation is showed in tab.1.

Coefficients			
X error (0.8)		Y error (0.2)	
Mean (0.7)	Dev. Std (0.3).	Mean (0.7)	Dev. Std (0.3)

Table 1: The coefficients for multicriteria analysis to research best topology for *net1* and *net2*.

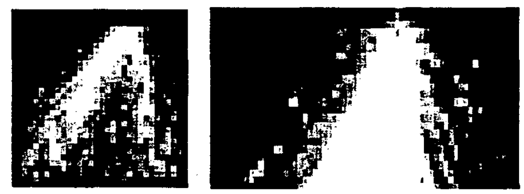


Figure 6: Selection of area of interest, and refining. Left: area of interest is marked by *net1*. Right: vertex identification by *net2* (dark point).

The topology obtained for *net1* consists of: two hidden layer with log-sigmoid transfer function, the first with 12 neurons and the second whit 6. The same topology has been obtained for *net2*, but the number of neurons in the hidden layers increases: 24 neurons in the first layer and 12 in the second one

A sensitivity analysis shoes if slight variation of the coefficients of the weights vary the weighted accuracy performance over a cross-validation set of image. A good network surely must have low coefficients sensitivity. An example of the application of *net1* and *net2* is showed in fig.6.

Vertex coordinates -identified with a mean error of about one pixel- permits a mean error lower than 2 degrees in processing the α, β, and γ angles. Fig.7 shows the processed angles in a standard image. This precision was tested over cross-validation images, and the system correctly classified all cut qualities in the corresponding images.

To test the robustness of the classification system, we simulated the industrial operation by adding different type of noise (gaussian, salt and pepper, multiplicative noises and the different image gamma correction) to the available images. The most important check deals with the α, β and γ error variation, because it directly impacts on the classifier accuracy. To degrade the classification performance it is necessary to inject synthetic noise densities much higher than noise densities typically present in real images. Results are shown in fig.8.

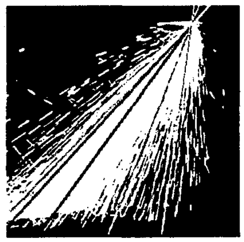


Figure 7: Result of application of linear regression algorithms combined with median filters to estimate the angles indexes.

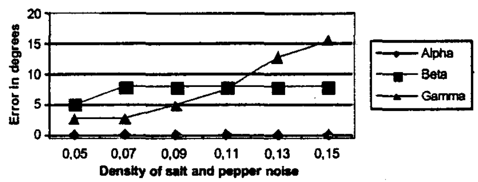


Figure 8: Mean errors for the processing of the angles in presence of salt and pepper noise at different density.

The noise analysis showed also that different tuning of the camera gamma correction affects the mean error of the γ angle. This effect can be understood by noting that different gamma corrections of the camera are themselves a sort of image preprocessing. High level of gamma correction tends to enhance the "nucleus" of the sparks jet, actually reducing the γ angle.

3. Conclusions

An automatic quality analysis measurement for laser cutting is presented. The combination of neural networks and traditional algorithms allows the system to achieve good accuracy. The system has a robust behavior with respect to different input condition and synthetic noise.

The paper presents also the preliminary evaluation of system demonstrator for quality measurement. Experiments have been performed by using Matlab on a monoprocessor system (Pentium II): with such a system the quality evaluation of a standard cut took about few minutes. This performance is obviously not acceptable for real time operation: however, the current system has not been optimized for performances since it was directed to demonstrate feasibility, accuracy and effectiveness of the proposed approach. A compiled optimized version, possibly running on DSP processors, will fulfill the real time constraint.

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