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Composite Techniques for Quality Analysis in Automotive Laser Welding

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Abstract *– Real-time monitoring of the laser-based applications is becoming a main issue for quality analysis in the steel manufacturing industry. The paper suggests a solution achieving an automated real-time quality inspection in laser welding applications. A composite system composed of soft-computing and traditional techniques has been considered for its positive impact on the reduced computational once compared with more traditional approaches.*

I. INTRODUCTION

Early detection of defects in metal manufacturing industries is becoming a main economical issue for its impact on quality analysis of the artifact and the industrial process.

Automated laser welding is having an increasing growth and diffusion due to the powerful and versatile process that allows for joining metals or non-metals at high speed with a relatively low heat input [1]. Lasers can produce welds in air, vacuum, controlled atmospheres, and pressurized chambers with a high reliable and automated process. Moreover, laser light may be focused to very small areas [2].

In general, the quality analysis of the process is assessed by offline inspection of each welded component. Such inspection phase is a time-consuming activity that rarely provides useful feedback to the expert user on how to improve the process itself (e.g., by tuning some parameters). In addition, external inspection of the welded artifact requires a costly procedure, most of times carried out with ultrasonic devices [3]. A different approach envisage an on-line quality analysis implemented directly during the process. A set of information is extracted from the sensors observing some critical parameters/phenomena associated with the process [4]. Following this philosophy we address the laser welding quality analysis with a self-tuning classification system that detects defects directly during the welding process. Moreover, the suggested procedure enables the process engineer to assess the quality of the process and study it aging effects for a subsequent process tuning. The quality analysis system is a composite system, namely a synergic composition of traditional algorithms for signal processing and soft-computing techniques [5]. During development of the solution we addressed not solely the performance issue (in terms of detected defects) but also the required computational burden in order to satisfy real-time requirements.

In particular, the industrial process under monitoring refers to the laser welding of automotive components carried out at the CRF-FIAT laboratories [17]. The specific test bed is a steel gear, a critical part in the gearbox for a passenger vehicle (see Figure 1).

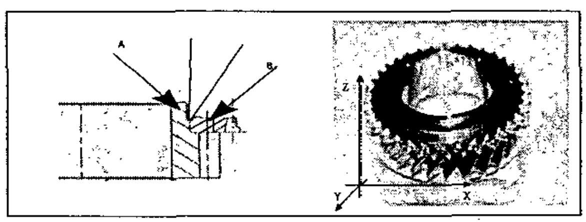

Fig. 1. The gear considered in our work.

Seven types of gear, built joining two rings (i.e., a light syncro gear and the principal gear), are actually butt-

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welded using a CO_2 laser. The test-bed is part of the Intelligent Manufactory Systems project SLAPS (Self-tuning and User-independent Laser Material Processing Units) [16] a European Union effort to advance the applied research on the development of intelligent laser processing unit [15].

The structure of the paper is as follows. Section 2 introduces a general background on laser welding and a description of the typical defects. Section 3 presents the features extracted from our industrial set-up and in section 4 is described the overall composite algorithm describing also the classifier selection, the tuning methodology and the experimental results.

II. LASER WELDING AND INDUSTRIAL SET-UP AT CRF LABS

The welding phenomenon can be defined as the localized coalescence of metals or non-metals produced by heat and/or pressure. Laser light may be focused to very small areas; this remarkable concentration of power can permit the welding process to occur.

Since a laser beam is a beam composed by light radiation, the reflective properties of metals tend to partially reflect the light and a big part of the incoming power can bounce back. This problem is compounded by the fact that the major industrial laser types emit infrared light, which metals reflect even better than visible light. This situation drastically changes when the surface melts. Liquid metals absorb much more power from the incoming radiation than solids do, so the heat flux absorbed suddenly increases, raising the metal's temperature above the boiling point and generating metal vapor. The pressure of this vapor opens a deep and narrow channel around the laser beam, forming what is called a keyhole. The aspect ratio (depth/width) of keyhole laser welds can be as high as 10:1 but is more commonly around 4:1. Keyhole welding is a threshold process: when the irradiant is low, very little power is absorbed. Once the irradiant is high enough to form a keyhole, most of the power is absorbed by the workpiece. Small power changes near the keyhole threshold will cause remarkable changes in the weld quality.

Lasers machines have the appreciated property to produce thin and deep welds, for that reason it is common to select the butt joint configuration for laser welding. The configuration allows for high speed and requires low heat in input because all the metal in the weld is being used to hold the assembly together (Figure 1). Regardless of the configuration, joint fit-up is critical in laser welding. Almost all laser welds are autogenous: no filler metal is used. Any gaps in the joint become undercuts in the finished weld. Even if undercuts are acceptable, a focused beam can pass through a butt joint with a 0.2 mm gap without welding it at all; the beam just bounces off the walls and out the other side. Moreover, the material being welded must be clean. Any non-metallic contaminants get ejected from the keyhole, producing spatter, porosity, and lens damage as well.

In our process we are interested in detecting both defects in welding and faults in the laser source. Typical defects can be classified as

- Penetration depth
- Misalignment of coupling in mounted samples
- Porosity (spontaneous and caused by misalignment or power lack)
- Decrease in laser power level (-10%) of laser source
- Power lack (t=10 ms) in laser source

The signals acquired during the welding process are: Laser Power (grid current) and Infrared radiation from the process. The experiments have been carried out by using the Rofin Sinar DC035 laser source [18].

The methodology presented to achieve the final quality classifier can be decomposed by three phases. The first is the Features extraction phase and can be carried out by applying traditional techniques from signals. The second phase is Feature reduction. It is extremely important since it can produce a compression of the dataset and permit to obtain less complex classifiers maintaining satisfied constrains on the accuracy of the classification system. The third phase is the Creation, Training and Validation of the classifiers.

In order to satisfy the real-time constrains, during the designing phases it is preferable to select fast and parallel processing, working directly on the samples of sensor signals in the time domain without a time consuming spectral transformation; in the classification phase we considered different kind of classifier with linear and non-linear components in order to achieve a good accuracy in classification by keeping bounded the computational load.

In this phase, the main characteristics we are interested in are accuracy and generalization over new samples, but we have some difficulties in achieving this result due to different causes:

- Few samples are available to tune the classifier
- Not all samples are correctly classified by the operator (there is an intrinsic error wit the process)
- The distribution of samples for the different error typologies is unknown.

To overcome these problems we consider an ad-hoc classifier specifically tuned to solve a specific class of welding errors. This choice allows to simplify the system and to support a parallel execution of the classifiers.

As we stated also in the previous section we are looking for a general automated framework for choosing of the optimal classifier, in terms of complexity and parameters, after a self-tuning process with few correctly classified samples. This process can be effectively solved by defining a set of suitable features, by mean of expert knowledge, and then automatically selecting the optimal classifier using self-tuning techniques.

III. DEFECTS AND FEATURE EXTRACTION

Concerning the detection of the power decrease or power lacks, the signal taken from the grid current on the laser possesses sufficient information to solve that task. Conversely, the signal from the photodiode is used to classify penetration, misalignment and porosity formation.

Due to the industrial environment, high frequency noise is present in the signals coming from the process; to separate the correct signal from the noise we did a spectral analysis in order to select the correct low-pass filter. A subsequent down-sampling operation has been done to reduce the dataset in order to speed up the feature extraction and classification.

Figure 2 shows the signals after being processed by the low-pass filtering. From the power signal (Figure 2.a) we extracted features referring to the mean intensity (**A**), and duration (**T**) of the useful part of the signal. Moreover, in order to detect lack in the power source we detect the greatest positive and negative deviation of the signal from its mean (respectively $\mathbf{F_1}$ and $\mathbf{F_2}$ in the figure) then synthesized in the maximum power fluctuation during the welding ($\mathbf{F_{max}}$).

From the original welding signal, before low-pass filtering, we extracted features referring to the mean intensity and variance; these indexes are used to classify penetration depth. After low-pass filtering, we build a local reference signal by cubic interpolation of the signal in order to extract features referring to porosities and misalignment. In Figure 2.b are present two main deviations, in terms of intensity, from the reference model; in detecting porosities we extract the time duration ($\mathbf{T_i}$) and the amplitude ($\mathbf{A_i}$) of the main five of these deviations. Moreover, the difference in between coordinates of minimum and maximum of the cubic model (**D** and **H**) are used to detect coupling misalignment (Figure 2.b, 4.b).

Figures 2, 3 and 4 show respectively signals related to correct and non-correct artifacts; it is possible to note, by a qualitative point of view, that the selected features can permit a sufficient discrimination between the error types. The complexity of the algorithms for the features extraction has been kept intentionally low in order to achieve real-time performances, so no spectral or computationally complex analysis has been computed in such a phase.

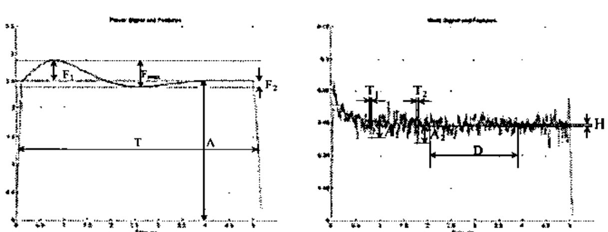

Fig. 2. Power (a) and welding (b) signals in a case of correct welding with selected features

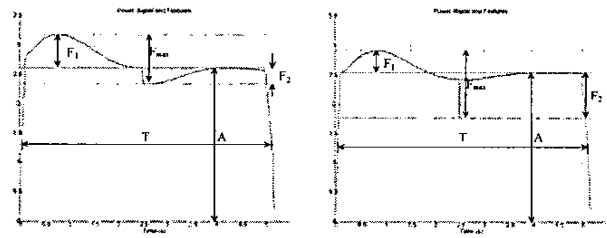

Fig. 3. 10% power decrease (a) and 10 ms power breakdown (b)

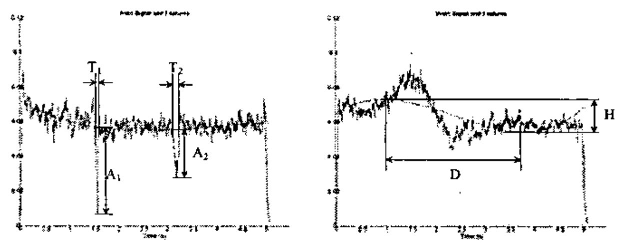

Fig. 4. Porosities (a) and misalignment errors (b)

IV. THE ALGORITHM

The structure of the classification algorithm is given in Figure 5. The algorithm is based on a hierarchical approach to detect as soon as possible welding defects. The gray blocks refers to signal processing activities where classical techniques are applied to extract features and the rounded highlight blocks represent soft computing classification modules (the remaining part of the algorithm is simple control logic that can be implemented by very low hardware complexity).

Power classification and penetration depth are classified independently from each other, mounting errors detection is performed only after their processing. If the sample is classified as "mounted correctly", then we activate the subsequent module for monitoring the possible presence of porosities.

To describe the complexity of non–soft computing part of the algorithm, for each signal processing and for the blocks used in the features extraction, we can use the big-O notation with respect to the number N of samples in the signal:

- Low-pass filtering: O(N)
- Laser Power Feature Extraction: O(N)
- Laser Penetration Features Extraction: O(N)
- Polynomial Fitting: O(N3)
- Mounting Feature Extraction: O(1)
- Porosity Feature Extraction: O(N)

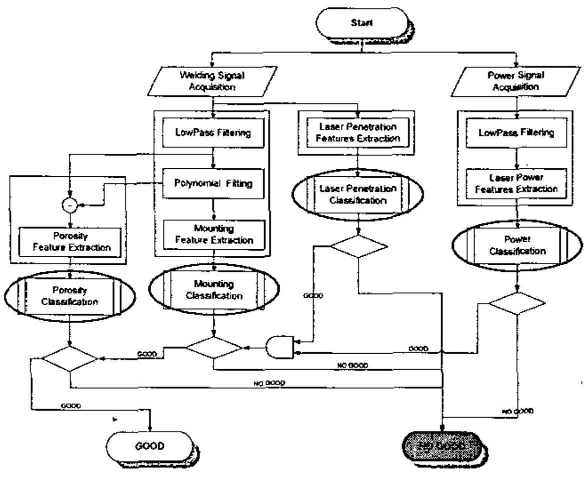

Fig. 5. The Algorithm

Once identified the relevant features the next step is to develop the classifier that, by processing the features implement the final quality analysis. The main problem with data classification is to acquire enough data correctly classified by human experts in order to design, tune and validate the classifier. We focus the attention on two families of classifiers: the k-nearest neighbor rule and feed-forward neural networks.

Due to its conceptual simplicity, the nearest neighbor rule (NN rule) has been used in a variety of classification applications [9]. The philosophy onto which the classifier relies is that a pattern is classified according to the majority of its nearest neighbor. Instead of considering the nearest neighbor only, one may take into account the k-nearest neighbors to estimate the class of an unknown pattern. An unknown pattern in input to the classifier is assigned to a particular class if either all of its k-nearest neighbors or at least the majority of its k-nearest neighbors belong to that class. In the first case, the classification of the unknown pattern can be refused if the k-nearest neighbors do not belong to the same class. In the second case, the classification can also be refused if the majority does not reach a specific quote. Detailed information on the nearest neighbor rule and its modifications can be found the in [8] and [9].

The neural classifier used for the classification is a feed-forward neural network with a hidden layer (the activation function of the neurons in the hidden layer is a hyperbolic tangent sigmoid and the activation function for the output layer in linear). The complexity of the classifiers depends on their structure; for neural networks, it depends on the number of neurons, for the k-nearest neighbor classifier, on the number of samples stored and the value of k. The number of inputs impacts directly on the complexity of both families.

Exploiting the physical knowledge of the process we extracted, from each signal, about six features to be classified. It is important to note that not all the selected features can contain the same amount of information with respect to the classification problem. We use an a-priori heuristic reduction to achieve the goal to keep low the computational load but maintaining a satisfactory accuracy. We try to detect, by means of classical KNN classification method, the relevance of each feature with respect the classification problem. In this way, we reduce the redundancy of the acquired information to reduce the complexity of the neural classifier. Using the k-nearest neighbor method with different k values and using the leave one out method [10] to estimate the performance of the classifier we identified the most relevant features for each error cause.

The topology of the neural network is designed by applying the cascade correlation algorithm [11] to the different error type classifiers. Both feed-forward neural network classifiers and k-nearest neighbor classifiers have been trained: in Figure 6 we plot the results obtained with the reduced set of features in terms of classification error on the validation set (mean and deviation over 100 different trials). The neural classifier has been created and tuned with a variable number of hidden neurons (from 1 to 10) selecting the most accurate one in validation. The plot shows that the classical and the neural classifier are comparable in performance, once the correct subset of feature is selected. In particular the best neural network is more accurate than the k-nearest neighbor classifier in the in the mounting error case. Moreover the best neural classifier has a maximal complexity of 4 neurons, noticeably lower with respect to the complexity of the corresponding classical classifier.

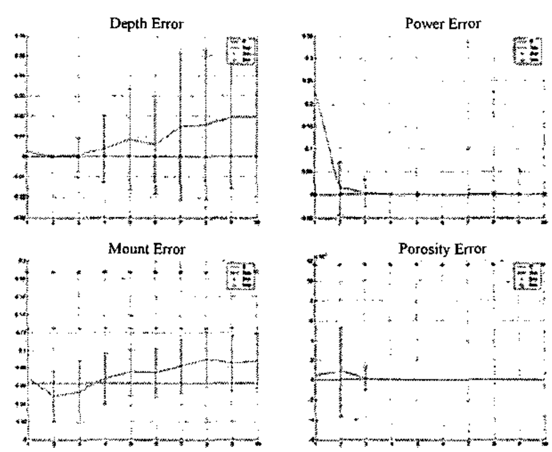

Fig. 6. Classification error and deviation of classifiers with feature reduction (horizontal axis: number of selected features).

To investigate the validity of feature reduction we reproduced the same classification experiments using the whole set of features for each error type leaving the cascade correlation method to investigate also more complex topologies. The results of this test reveal no noticeable difference in the classification error thus confirming the a-priori choice of relevant features made by the off-line test.

In the training phase we uses part of the available data to train the network and the rest for cross-validation and topology selection. The training is performed using the Levenberg-Marquardt algorithm [12] and the data are preprocessed by normalization and rescaling in order to speed-up the learning phase [13].

Due to small amount of samples available, it is also possible to use the majority of sample for the training phase and obtain a statistical bound (by confidence intervals) for the estimated accuracy of the best classifiers performance. By applying the Bayesian approach we estimate the probability of error and it confidence intervals. The 5%-level confidence interval bounds are plotted as function of N. Using the plot in Figure 7 we implicitly assume the hypothesis that the cross-validation subset is independent from the training set and the N patterns effectively are an i.i.d sample.

The final results of the training phase for our tests are presented in table 1. The table shows for each error type (depth, power, mount and porosity) the composition of the training and validation subsets, the best result in accuracy for the two families (k-nn and neural classifiers) and the corresponding intervals of confidence.

In the case of feed-forward neural networks, the most accurate network in cross-validation has been selected over 100 different experiment with different initial weights initialization

Theoretically, when a classifier is given, we must achieve the maximum likelihood estimator for the probability of error $\hat{\varepsilon}$, by drawing a random sample of size N from the data distribution, and applying the classifier to it:

$$\hat{\varepsilon} = \tau / N$$

where τ is the number of misclassified samples. Given $\hat{\varepsilon}$ it is possible to compute the confidence intervals between the real error and the estimated error $\hat{\varepsilon}$ (numerically tabulated for the level of confidence $\gamma = 0.95$ in Figure 7). In the horizontal axis there is the true error ε, and the vertical axis is the estimated error $\hat{\varepsilon}$.

In this paper we present the preliminary evaluation of the system for quality measurement (experiments have been performed by using Matlab on a Pentium III monoprocessor system). Since the complexity and memory occupation for feed-forward neural networks is lower with respect of KNN classifiers we choose for all the error type detection the best neural classifier obtained. With such a system the quality evaluation of a standard welding took about 3 seconds.

Table 1. Experimental results

	Classifier	Training	Cross Validation	Error of best classifier	Accuracy Interval	Notes
Depth	KNN	40 samples (100%)	39 samples (~100%)	0 %	~ 0–10 %	K= 1
	FF-NN	28 samples (70%)	12 samples (30%)	0 %	~ 0– 10 %	Neurons= 2 (Best over 100)
Power	KNN	69 samples (100%)	68 samples (~100%)	0 %	~ 0 – 8 %	K= 1
	FF-NN	48 samples (70%)	21 samples (30%)	0 %	~ 0 – 8 %	Neurons= 4 (Best over 100)
Mount	KNN	55 samples (100%)	54 samples (~100%)	1.8 %	~ 0– 10 %	K= 1
	FF-NN	39 samples (70%)	16 samples (30%)	0 %	~ 0 – 8 %	Neurons= 2 (Best over 100)
Porosity	KNN	215 samples (100%)	214 samples (~100%)	0.35 %	~ 0 – 4 %	K= 1
	FF-NN	199 samples (70%)	86 samples (30%)	0 %	~ 0 – 4 %	Neurons= 4 (Best over 100)

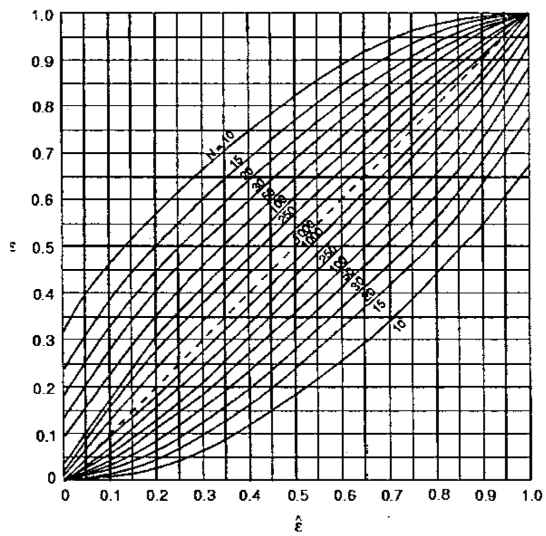

Fig. 7. Confidence interval for $\gamma = 0.95$

V. CONCLUSIONS

An automatic quality analysis self-tuning measurement approach for laser welding is presented. The combination of neural networks and traditional algorithms allows the system to achieve good accuracy keeping bounded the whole computational load.

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