

Compound techniques for quality analysis in automotive laser welding

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Abstract

In this paper we present an industrial application of soft-computing and classical techniques in laser welding real-time monitoring and propose a solution to automate the on-line quality measurement using neural networks and standard pre-processing techniques. The trade-off between accuracy and robustness versus complexity was considered in order to achieve a prototype solution working in real time. The whole monitoring system exploits self-tuning capabilities of neural networks to obtain an application independent tools for laser welding real-time monitoring.

Keywords: *Soft-Computing, Neural Networks, Laser Welding, Real-Time Monitoring, Quality Analysis.*

1. Introduction

Early detection of defects in metal manufacturing industries, in particular in the metal welding field, and measurement of process quality are becoming one of the key issues regarding the important economic impact over the industrial process.

All over the world automated laser welding is having an exponential growth and diffusion especially in the automotive industry [1]. Laser welding is a powerful, versatile process that joins metals or non-metals at high speed with relatively low heat input. Lasers can produce welds in air, in vacuum, in controlled atmospheres, and in pressurized chambers, and this process is easily automated and highly reliable. Moreover laser light may be focused to very small areas [2]

Presently, the quality of the whole process is assessed by offline inspection of each welded component. The inspection phase of components is a time-consuming activity that rarely provides useful feedback to process set-up and tuning. Moreover, it is not easy to inspect the welding from the outside without using expensive techniques like ultrasonic waves [3]. Recently, some researchers are investigating correlation between the values of sensors with different spectral sensitivity and the resulting welding [4]. Starting from this approach, the aim of our research is to implement a self-tuning quality classification system to detect defects generated during the welding process without any further off-line inspection of components. This can be considered as a real-time monitoring apparatus for laser welding in industrial

processes independent from the particular application and suitable for off-line self-tuning given a set of correctly classified samples.

Real-time monitoring enables to identify defects formation during the welding, thus detecting incorrect component without any further cost in quality analysis. In addition, the on-line monitoring of process parameters enables the process engineers to correctly tune the process window by means of the feedbacks provided by the defect detecting system, thus notably increasing the overall process quality.

From the industrial point of view, we are interested in a quality measurement system with both high performance, in terms of detected defects, and low computational load in order to satisfy real-time requirements. To achieve this trade-off, obtaining also self-tuning capabilities, we have designed a compound system: a synergic composition of traditional algorithms for signal processing and soft-computing techniques for classification [5]. Since we do not have an analytical model of the process, this kind of system extracts suitable indexes describing the signals taken from the process and then, by means of those indexes, uses soft-computing techniques (i.e., neural networks) to classify the welding. We are interested in few compact high-level features capable of compressing relevant information about the ongoing welding process; such features are deduced both from expert knowledge in welding monitoring and from statistical analysis of classified training samples.

The industrial process considered in our paper refers to laser welding of automotive components at Centro Ricerche FIAT laboratories (CRF [W1]), and the specific test bed is a steel gear from FIAT, as it is already manufactured in mass production (see Figure 1). This gear is a critical part in the gearbox for a passenger vehicle; seven types of gear, built joining two rings (i.e., a light synchro gear and the principal gear), are actually butt-welded using a CO₂ laser. In the current production process, every product is tested using ultrasonic waves after welding. This particular test-bed is part of the Intelligent Manufactory Systems (IMS [W2]) project Self-tuning and User-independent Laser Material Processing Units (SLAPS [W3]) a worldwide international effort for the development of intelligent laser processing.

In the next section we present the general background on laser welding and a description of some the error causes in the typical industrial process; after that, we analyze the CRF industrial set-up and the errors we are interested in detecting for this particular test-bed. In section 3 we present the features extracted from the industrial set-up and section 4 describes the overall compound algorithm highlighting the classifier selection and tuning methodology. Experimental results are presented in section 5 and future work is presented with conclusion in section 6.

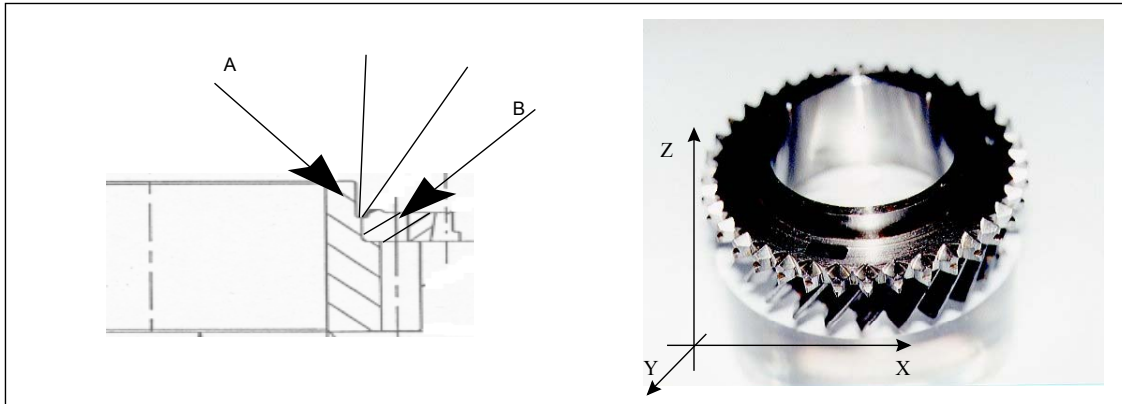


Figure 1: The gear considered in our work.

2. Laser welding and industrial set-up at CRF Labs

A weld is defined as a localized coalescence of metals or non-metals produced by heat and/or pressure. This definition describes a wide range of processes including soldering, brazing, and fusion welding. Lasers are used for all of these, but in our study we focus on fusion welding.

Laser light may be focused to very small areas. This concentration of power is necessary for the welding process to occur. Laser beam is a light beam, and metals are very good reflectors of light. This problem is compounded by the fact that the major industrial laser types emit infrared light, which metals reflect even better than visible light. As a result, most of the incoming power bounces right back at the source as indicated. Once the surface melts, everything changes. Liquid metals absorb much more light than do solids, so the heat input suddenly increases, raising the metal's temperature above the boiling point and generating metal vapor. The pressure of this vapor opens a channel around the laser beam, forming what is called a *keyhole*. A fully developed keyhole traps almost all of the incident laser power and converts it into heat. Some of the light is absorbed by the vapor, while the rest bounces around inside the channel and delivers energy with each reflection. The keyhole allows lasers to produce welds that are deep and narrow, because power is delivered to the work through the vapor channel. 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 work. Small power changes near the keyhole threshold will cause remarkable changes in the weld.

Where butt joints are practical, they allow the greatest speed and the lowest heat input because all the metal in the weld is being used to hold the assembly together. Regardless of the configuration, joint fit-up is critical in laser welding. Because lasers are capable of producing thin, deep welds, it seems natural to select a butt joint configuration for laser welding. Almost all laser welds are autogenous: no filler metal is used. It is very difficult to get filler into the tiny melt zones that most lasers produce. 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. This is a good idea for all welding, but more important for laser welding. Any non-metallic contaminants get ejected from the keyhole, producing spatter, porosity, and lens damage as well.

For the CRF set-up, we are interested in a limited number of aspects, among all the possible error causes. Since the whole system has the twofold goal of welding quality assessment and monitoring of the welding process, we are interested in detecting both defects in welding and faults in the laser source. In particular they are:

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

The penetration depth has been evaluated by considering different techniques presently investigated in welding literature [6] [7]. The best results, after several experiments, have been obtained by the CO₂ back reflected light analysis. Besides, by this technique, we can also detect defects like holes on the surface (e.g., by means of fast variations in the signal) and misalignment of components.

Figure 2: The industrial set-up

The signals acquired during the process refer to the laser power (grid current) and IR radiation from the process (340 nm).

Applying standard techniques, we extract from these signals the high level features to be used by soft-computing based classifiers in quality assesment. In this phase, we are interested in a fast parallel processing, working directly on the samples of sensor signals in the time domain without any time consuming spectral analysis. In the following classification phase we consider different kind of classifier with linear and non-linear components in order to achieve a good accuracy by keeping bounded the computational load. The main characteristics we are interested in are *accuracy* and *generalization* over new samples, but we have some difficulties in achieving this results due to different causes:

- Few samples to tune the system
- Not all samples are correctly classified by the operator
- The distribution of samples for the different error typologies is not uniform

To overcome classification problems deriving from these causes, in our system we use an ad-hoc classifier (i.e., k-nearest neighbor or feed-forward Neural Network) specifically tuned for each error category and we apply a stratified training in order to balance the distribution of the samples for each typology (i.e., the proportion of samples from each class in all data partitions for cross-validation is the same as in all data). This choice allows the system to be highly parallel also in feature classification, thus obtaining the required real-time behavior and an opportune separation of concern in detecting the error causes. Moreover, this approach provides a useful feedback for process control and tuning.

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. Defining a set of suitable features, by mean of expert knowledge, and then automatically selecting the optimal classifier using self-tuning techniques can effectively solve this process.

3. Defects and feature extraction

As previously stated, we approach the complexity of welding monitoring by separating the different error causes and using ad-hoc classifiers tuned on few correctly classified samples. We actually use the signal taken from the grid current on the laser source to detect power decrease or power lacks. The signal from the photodiode is used to classify penetration, misalignment, and porosity formation.

Due to the industrial environment, there is a lot of high frequency noise over the real process signals; to separate the correct signal from the noise we did a spectral analysis in order to select the correct low-pass filter and then down sample the obtained data in order to speed up the feature extraction and the sample classification.

Figure 3 shows the signals taken from the industrial set-up after low-pass filtering and features extraction. From the power signal (Figure 3a) 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 **F₁** and **F₂** in the figure) then synthesized in the maximum power fluctuation during the welding (**F_{max}=F₁+F₂**).

From the original welding signal, before low-pass filtering, we extract features referring to the mean intensity (**M**) and variance (**S**); 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 3b it is possible to notice two of the main deviations, in terms of intensity, from the reference model; in detecting porosities we extract the time duration (**T_i**) and the amplitude (**A_i**) of the main five of these deviations. Moreover, the differences in between coordinates of the stationary points in the cubic interpolation (**D** and **H**) are used to detect coupling misalignment.

From the experimental data we have analyzed and expert knowledge, we consider that the features previously described are strictly related to the defects we are interested in. In Figure 4 and Figure 5 you can see how the features previously described represent the possible errors in welding regarding power errors, porosities, and misalignment. As you can notice from the plots, the extracted features represent good synthetic index in order to promptly detect defects formation. 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 complex analysis has been computed in such a phase.

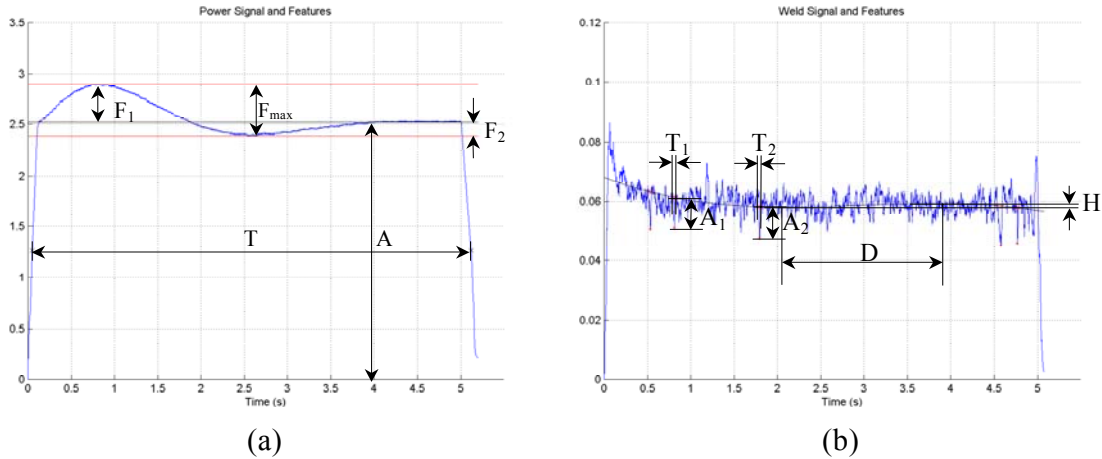


Figure 3: Power (a) and welding (b) signals for a correct welding with features

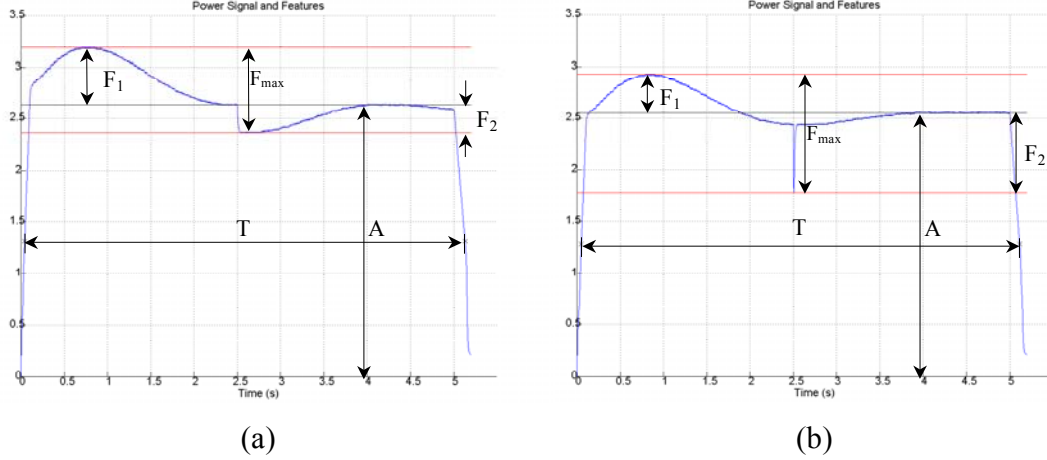


Figure 4: 10% power decrease (a) and 10 ms power breakdown (b)

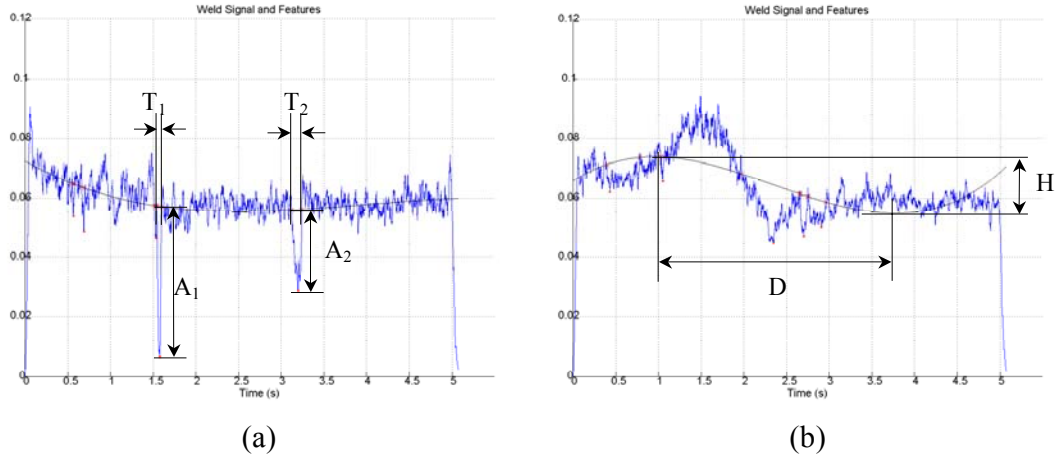


Figure 5: Porosities (a) and misalignment errors (b)

4. The Algorithm

In Figure 6 we present the whole monitoring algorithm. As you can notice it is highly parallel and uses a hierarchical approach in order to detect as soon as possible defects in welding and in order to keep isolated the different error causes thus allowing a useful feedback to the people involved in process tuning and maintenance.

Signals acquired from sensors are separately elaborated in a pipelined process in order to speed-up features extraction; the computational load has been reduced by extracting features referring to the time evolution of the process signals without any heavy analysis in the frequency domain. In the figure gray blocks refers to signal processing activities, where classical techniques are applied to feature extraction, the blocks with the rounded highlight represent soft computing classification, and the rest of the algorithm is composed by simple control logic with no computational cost. From the diagram, we notice how power classification and penetration depth are classified independently and that mounting classification is performed only after them. If the sample is classified as “mounted correctly”, then it is possible to classify features referring to porosities in the next stage.

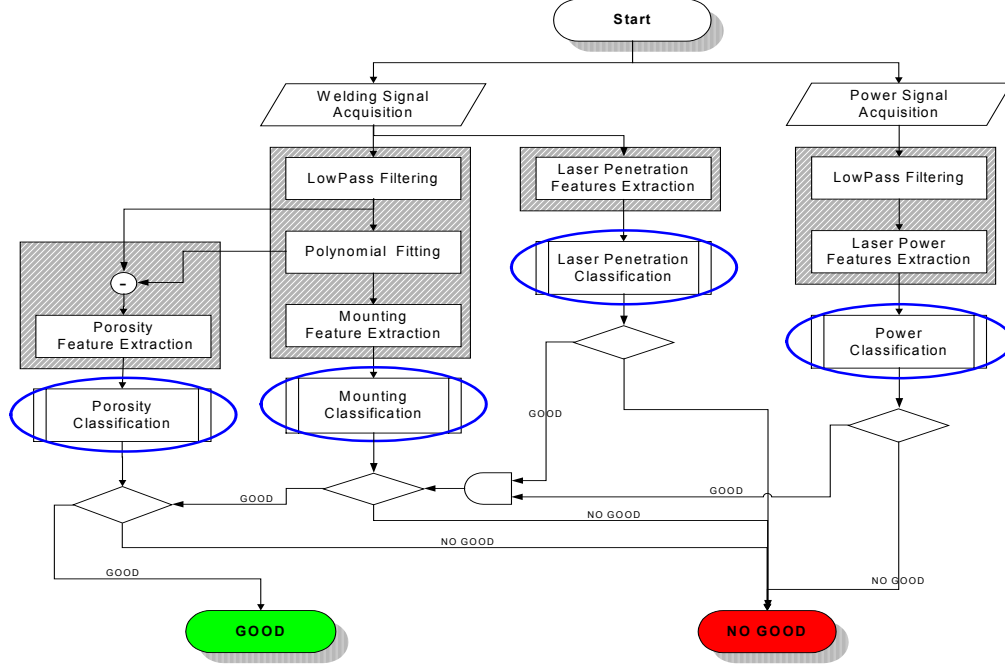


Figure 6: The Algorithm

To give an idea of the complexity for the classical part of the algorithm we identify, for each signal processing building block used in feature extraction, an approximate complexity index using 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: $O(N^3)$
- Mounting Feature Extraction: $O(1)$
- Porosity Feature Extraction: $O(N)$

Obviously these complexities are computed for the worst case and the algorithms used in the first prototype they refer to are not optimized. For the second part of the algorithm, we tested two different kinds of classifiers: the *k-nearest neighbor rule* and *feed-forward neural networks*.

Due to its conceptual simplicity, the nearest neighbour rule (NN rule) has been used in a variety of classification applications. The idea of this rule is that, given a set of training data with particular pattern classes, an unknown pattern receives the class of its nearest neighbour. The nearest neighbour has to be determined using some N -dimensional metric (e.g., the Euclidean distance) where N is the number of features per pattern. To be more robust to out-layers and noise in the training set, one may take into account the k nearest neighbours to estimate the class of an unknown pattern instead of considering only the nearest neighbour. The term KNN rule is used to refer to this classifier. The KNN rule is equipped with an additional degree of freedom. An unknown pattern is assigned a particular class if

1. either all of its k nearest neighbours
2. or at least the majority of its k nearest neighbours belong to that class

in the first case, the classification of the unknown pattern can be refused if the k nearest neighbours 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

neighbour rule and its modifications can be found in the famous books of Niemann [8] and Ripley [9].

The neural classifier used for the classification is a feed-forward neural network with a hidden layer. The number of neurons in the hidden layer depends on the specific error cause and it is incrementally learned. The activation function of the neurons in the hidden layer is a hyperbolic tangent and the activation function for the output layer is a sigmoid. We use a *1-out-m* coding for the output: each output codes a different class and the target output is 1 for the n^{th} output and 0 for the others if the sample belongs to class n .

The complexity of a classifier depends on its structure; for neural networks, it depends on the number of neurons, for k-nearest neighbor it depends on the number of samples stored and the value of k . As a rule of thumb you can consider a 5NN classifier 1000 times more complex than a neural one with 12 neurons in terms of time and memory occupation.

5. Classifiers training and experimental results

The main problem with data classification is to acquire enough data correctly classified by human experts. In our case we have only few samples to implement the self-tuning phase and they are not always confidently classified. This means that we know exactly the error cause for part of the training data and for the rest we suppose no classification at all. In Table 1 we report the number of samples for each error category and classification.

From each signal we extract about six features to be classified. To keep a low computational load also in the classification part of the monitoring task, we use an a-priori heuristic to reduce the number of features used in the final prototype. We try to detect, by means of classical KNN classification method the relevance of each feature with respect to the error cause. By doing so, we reduce the redundancy of the acquired information and, by means of that, we reduce the complexity of the final classifier. Using the k-nearest neighbor method with different k values to each possible combination of features and using the *leave one out* method [10] in order to predict an error expectation we determine for each error cause the features that most identify them.

In figure from 7 to 10, we represent the features space for each error cause by choosing the best two predicting features selected by the off-line feature reduction algorithm; circles represent correct samples, crosses represent errors and dots represent unclassified samples. As you can see from the pictures the features selected by this reduction process already separates each class by keeping the classification problem solution obtainable at a low computational cost.

We are interested in the use of feed-forward neural networks as classifiers for their low implementation complexity and we are interested in comparing them with classical k-nearest neighbor classifiers from the generalization point of view. During the training phase we divide the samples in two sets: training set and validation set. The former is used to train the neural classifiers and the latter is used to estimate the generalization error of the learned classifier. We use the same splitting with different k-nearest neighbor in order to compare the two approaches.

	Good	No Good	Not Classified	Total
Depth Error	31	9	29	69
Power Error	29	40	0	69
Mount Error	47	8	14	69
Porosity Error	275	10	60	345

Table 1: The available data

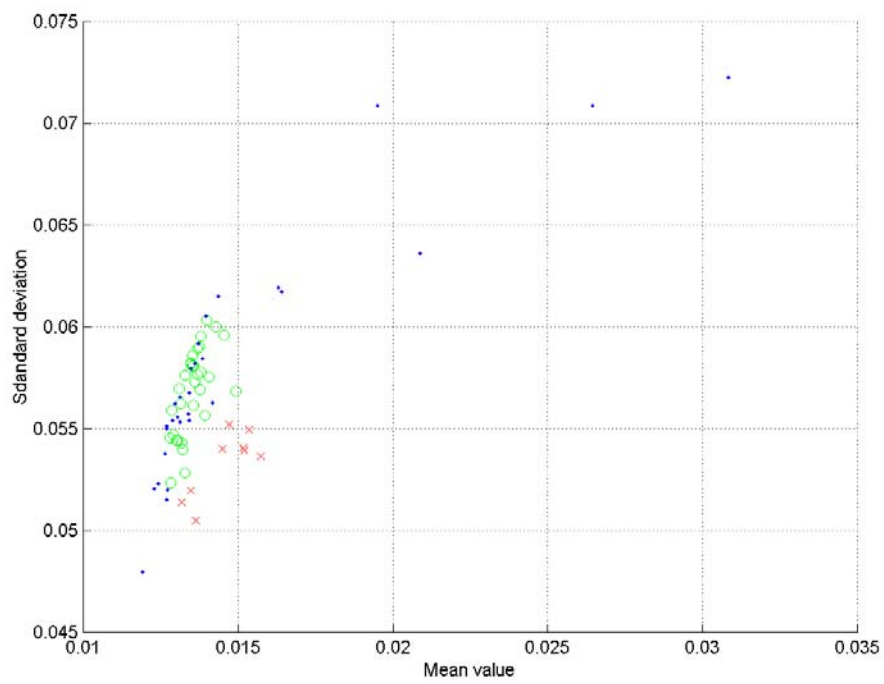


Figure 7: Depth error (reduced) feaure space

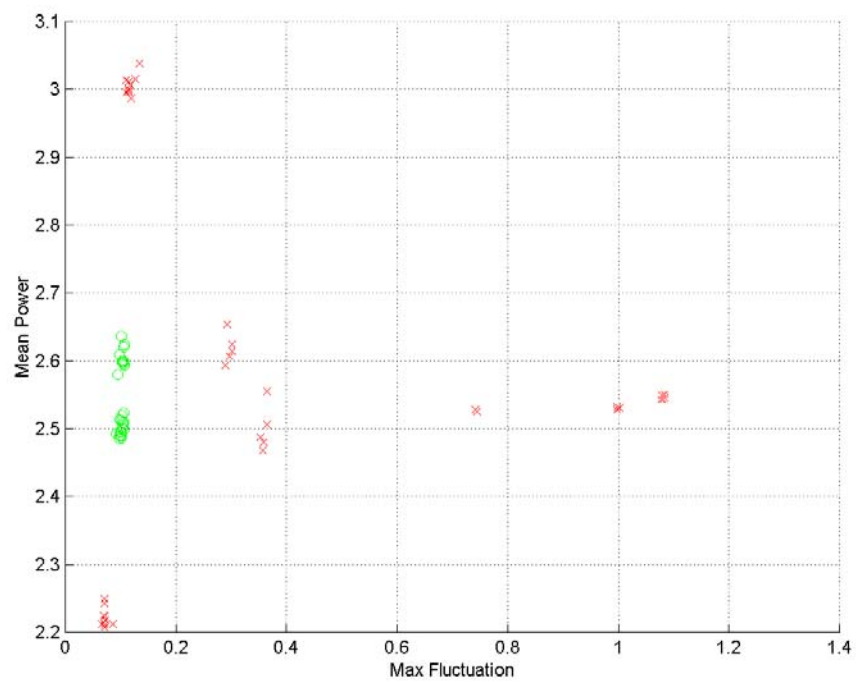


Figure 8: Power error (reduced) feature space

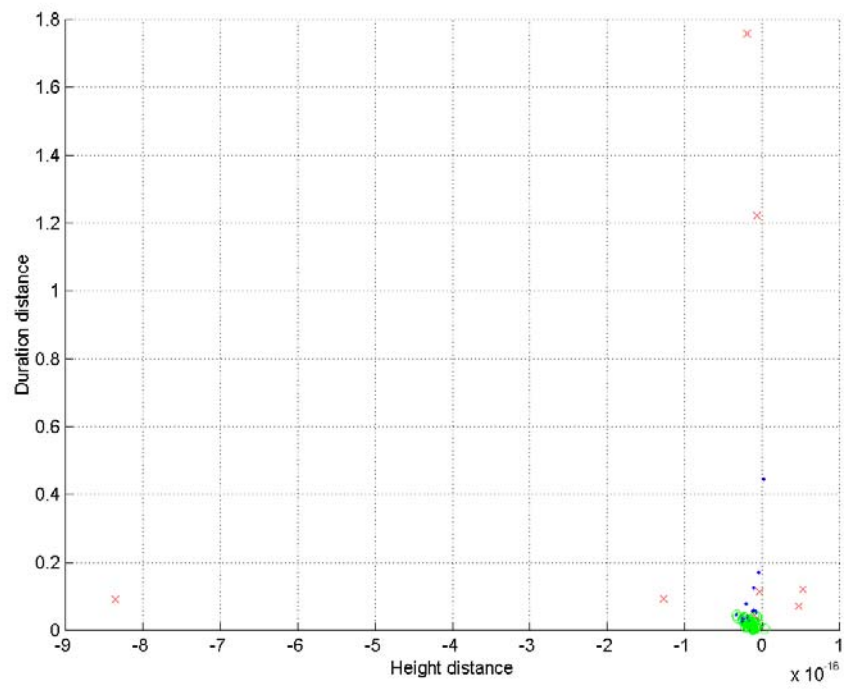


Figure 9: Mount error (reduced) feature space

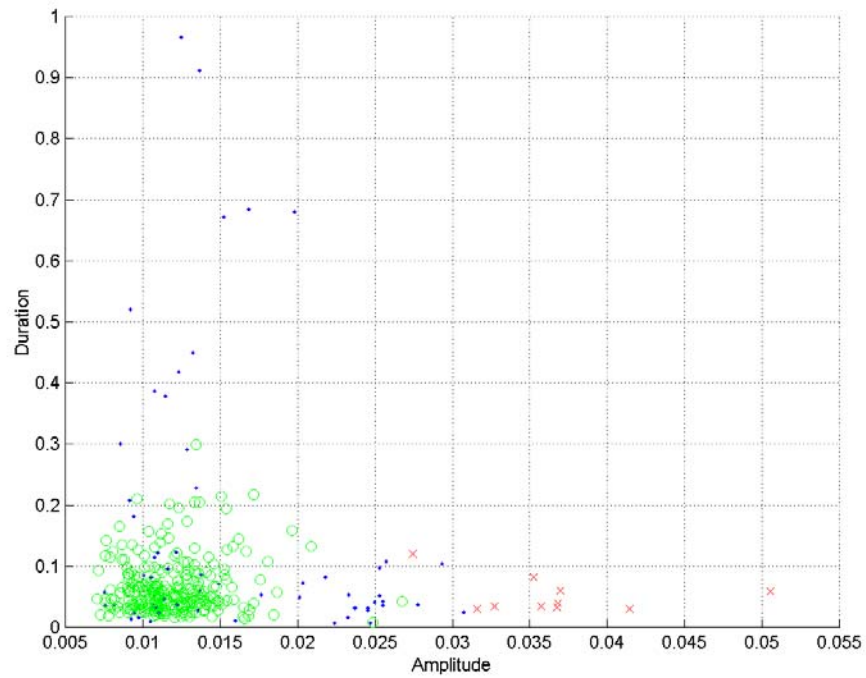


Figure 10: Porosity error (reduced) feature space

The topology of the neural network is designed by applying an incremental approach for each of the different error classifier. In Figure 11 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) for the neural classifier with a variable number of hidden neurons (from 1 to 10). From the plot you can see how the mean results with classical classifiers and neural network are comparable, but, once selected the correct number of hidden neurons, the best neural network obtain better result with respect to k-nearest neighbor especially in the mount error case. Moreover the best neural classifier has a maximal complexity of 4 neurons, noticeably lower with respect to the complexity of the corresponding k-nearest neighbor classifier. The training is performed using the Levenberg-Marquardt algorithm [11] and the data are preprocessed by normalization and rescaling in order to speed-up the learning phase [12].

To investigate the validity of feature reduction we reproduced the same classification experiments using the whole set of features for each error cause leaving the cascade correlation 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.

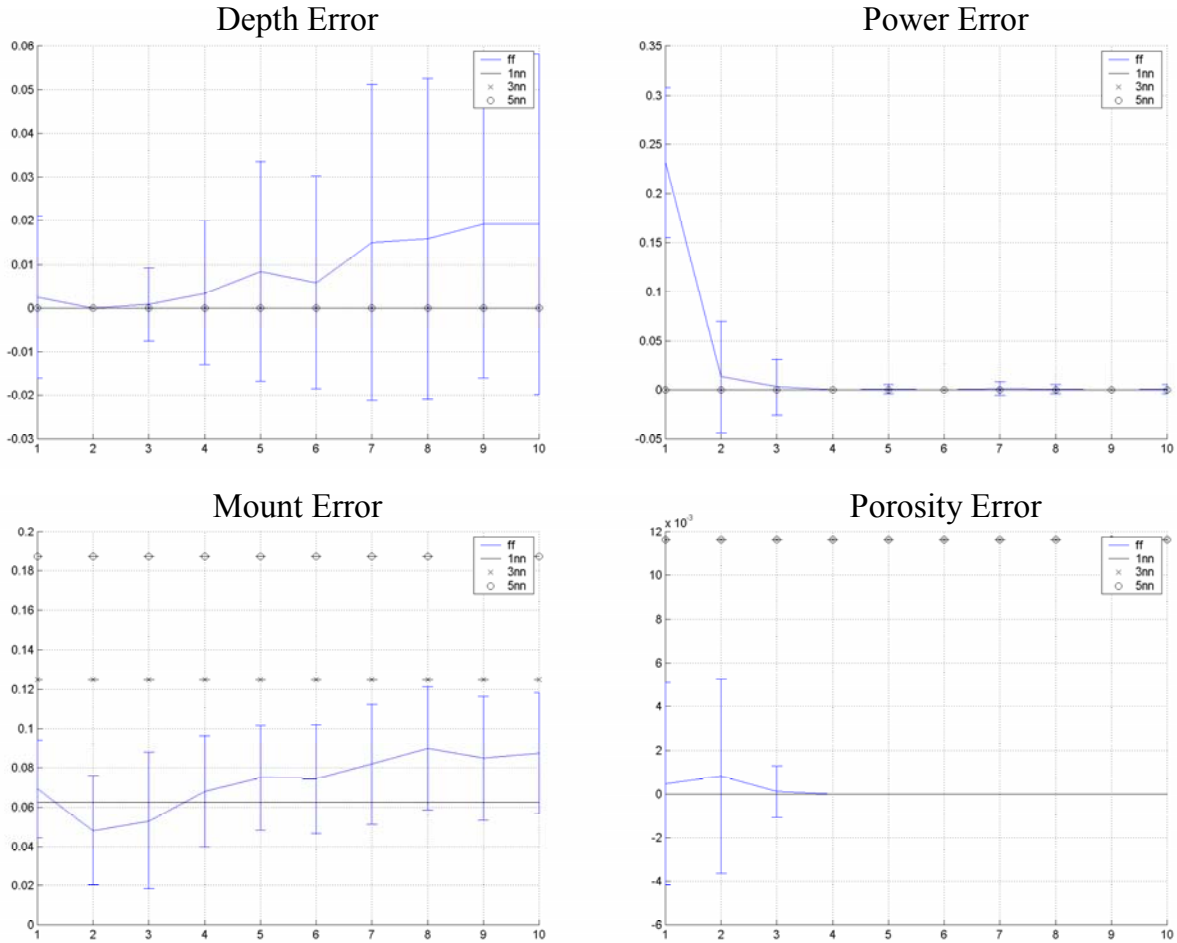


Figure 11: Classification error with neural and classical classifiers with feature reduction

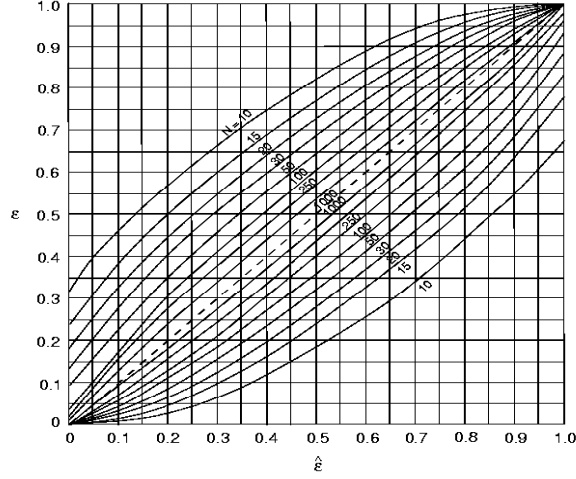


Figure 12: Confidence interval for $\gamma = 0.95$

Due to the few samples used in our experiments, the performance of best classifiers has a statistical bound in confidence intervals for the estimated accuracy. By applying the Bayesian approach we estimate the probability of error and its confidence intervals. When a classifier is given we can estimate the probability of error $\hat{\epsilon}$ by drawing N samples randomly and applying the classifier to them. When τ is the number of misclassified samples and N is the number of total random samples, the maximum likelihood estimator for the probability of error is given by:

$$\hat{\epsilon} = \tau / N.$$

Given the density of the estimated error it is possible to compute confidence intervals between the real error and the estimated error $\hat{\epsilon}$ numerically tabulated for the level of confidence $\gamma = 0.95$ in Figure 12 [13].

The final results of the training phase for our test-bed, with accuracy intervals, are presented in Table 2. Since the complexity and memory occupation for feed-forward neural networks is lower with respect of KNN classifiers we choose for all the error causes the best neural classifier obtained. In this paper we are presenting the preliminary evaluation of the system for quality measurement; experiments have been performed by using Matlab on a monoprocessor system (Pentium III): with such a system the quality evaluation of a standard welding took about 3 seconds.

6. Conclusions & Future Work

In this paper we presented an industrial application of soft-computing and classical techniques in laser welding real-time monitoring and propose a solution to automate the on-line quality assessment and welding process monitoring. The combination of neural networks and traditional algorithms allows the system to achieve good accuracy keeping bounded the whole computational load.

The whole monitoring system exploit self-tuning capabilities of neural networks to obtain an application independent tools for laser welding real-time, but needs to be tested in real industrial plants. The next stage of project we presented in this paper is to implement the algorithm on a dedicated hardware and to validate it on the real industrial process. The present system has been patented in Europe and its validity is being extended to USA [14].

	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)

Table 2: Experimental results

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- [W3] SLAPS (Self-tuning and User-independent Laser Material Processing Units) <http://www.slaps.org/>
- [W4] <http://www.rofin-sinar.com/>