Nozzles Classification in a High-Pressure Water Jet System

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***Abstract*—In this paper, a technique for classifying the working condition of a water jet system is presented. The classifier is based on the discrete Fourier transform (DFT) of the electrical power signal. It is shown that this information can characterize the working condition of the system and predict the presence of (an incoming) faulty behavior. Experiments and comparisons with the 1-nearest-neighbor (1-NN) classifier have been carried out, showing promising results.**

***Index Terms*—Classification, diagnosis, water jet (WJ) systems.**

I. Introduction

WATER JET and abrasive water jet (WJ/AWJ) technology presents some particular characteristics that make it suitable in application fields where particular manufacturing operations on special material are required; machining activities such as cutting hard to machine materials (e.g., steels, titanium alloys, aluminum alloys, brittle materials) or carrying out operations such as turning and milling as well as surface treatments such as peening, cleaning, decoating, and descaling represent some of the possible applications of WJ/AWJ technology.

The AWJ cutting process has the peculiarity that it is a cold process as the water takes heat away from the interested area of the work piece. This characteristic is very important because it allows to work without damaging the metallic material structure.

Starting from the simple consideration that the acquired electric signals give useful indications for diagnosis purposes [1], it is a little step to consider a continuous nonintrusive on-field monitoring activity during all the plant components' life.

It is well known that a very important part for the definition of the efficiency of these systems is the water nozzle; in effect, this component plays an important role in the definition of the overall efficiency, which is measured as the ratio between the available fluid-dynamic power and the electric active power from the network. Hence, monitoring the efficiency of the nozzle allows predicting the efficiency of the overall AWJ system.

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In the aforementioned paper, a comparison between the performances of different nozzles in terms of the electric power necessary to carry out the same mechanical operation has been reported. Different power consumptions lead to differences, sometimes relatively large, in terms of cutting performance as well as operating cost of the system. Moreover, it is shown that it possible to extract information on the behavior of the plant from the power signal; this could allow detecting and foreseeing wrong operating conditions.

This paper aims at setting up a technique for extracting information from the electrical power signal about the working condition of the system. In particular, we are interested in both identifying the nozzle type and its working condition by means of a signature for each nozzle in each working condition that allows the correct classification.

The availability of suitable signatures allows building up a nozzle footprints database. Such a database constitutes the knowledge for the automatic recognition of the mounted nozzle and its working condition. All these aspects will be discussed further in the following sections.

II. System Architecture

The WJ technology is characterized by phenomena belonging to different fields of physics. The utilized WJ system will be briefly described here using the schema in Fig. 1. The main components of a WJ cutting system are depicted. Considering a complete WJ cutting system, electrical energy is provided at first to the 380 V–50 Hz three-phase induction motor that pressurizes the oil by means of the radial pistons oil pump. The pressure reaches a value of 20 MPa in the oil circuit.

The oil provides its hydraulic energy to water by means of the double-acting intensifier, as depicted in Fig. 1: at this stage, the energy means of transport changes, and due to the increasing pressure (which reaches 400 MPa), the compressibility of water has to be considered. An accumulator reduces the water pressure fluctuations [1]–[6]. When water reaches the cutting head and flows through the orifice, the pressure energy changes into kinetic energy, and the jet is formed. Further, when AWJ is considered, solid particles join the WJ inside the mixing chamber, being entrained by the air flow generated by the jet itself. In this case, the kinetic energy of abrasive particles is dramatically increased due to the exchange of momentum with water inside the mixing chamber and the focusing nozzle.

The AWJ cutting quality typically depends on the process parameters selection (i.e., water pressure, abrasive mass flow

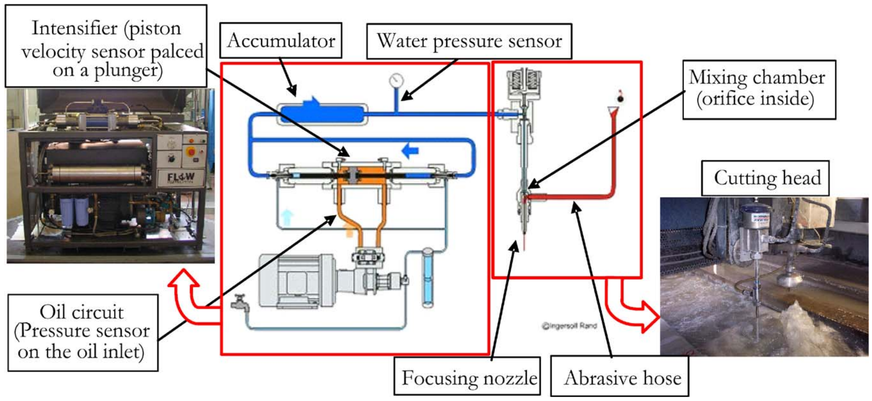

Fig. 1. Main components of the WJ cutting system (scheme in the middle by Ingersoll Rand; photographs by Politecnico di Milano).

rate, abrasive granulometry, cutting head feed rate, and standoff distance) as well as on the fluid-dynamic parameters, such as the orifice and focuser diameters and the mixing chamber geometry. In addition to the aforementioned parameters, which are considered as directly valuable variables, some external factors exist and play a non-negligible role on the cutting quality in terms of roughness and waviness, such as water pressure fluctuation due to the alternate motion of the pumping system, abrasive mass flow rate fluctuation, workpiece and fixturing system vibrations, and granulometric distribution of the abrasive particles.

To monitor the complete WJ cutting system, a digital-signal-processor-based system has been defined. In particular, the plant has been equipped with sensors to acquire the signals of the most relevant parameters describing its behavior: oil pressure, water pressure, and piston velocity.

Electrical motor signals are acquired by an analog-to-digital conversion board with simultaneous sampling up to 200 kHz sampling rate on a single channel with a 16-bit resolution.

Voltage and current transducers have been specially realized to adapt the signal levels to the analog-to-digital converter and to ensure an adequate insulation level among channels and between the supply and measuring devices over a wide band.

III. Pattern Recognition (PR)

Object recognition, description, and classification are very important tasks for the daily life [7]–[9]. In particular, PR is the scientific discipline dealing with methods for both object description and object classification. Applications of PR techniques are numerous and cover a broad scope of activities; e.g., crop analysis, soil evaluation, analysis of telescopic images, automated spectroscopy, automated cytology, genetic studies, traffic analysis and control, assessment of urban growth, fault detection, character recognition, speech recognition, automatic navigation systems, pollution analysis, seismic analysis, analysis of electrocardiograms, analysis of electroencephalograms, analysis of medical images, detection and classification of radar and sonar signals, automatic target recognition, identification of fingerprints, surveillance systems, and so on. It is important to note that the patterns to be analyzed and recognized can be signals, images, or plain tables of values. PR approaches are based on the notion of similarity: between two

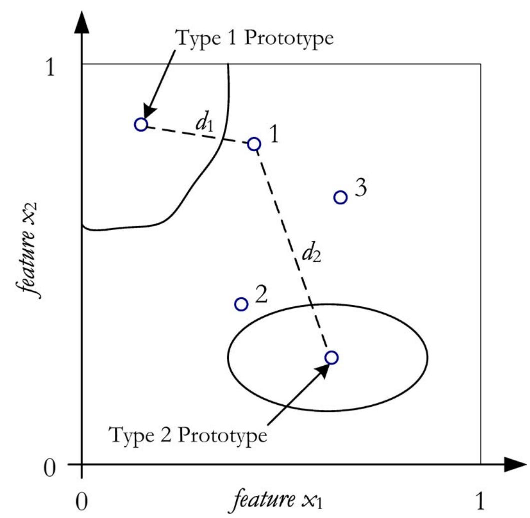

Fig. 2. $f_1 - f_2$ plane. Euclidian distances are also depicted on the plane. Classification of object 1 or 2 is a simple task. However, classification of point 3 is a more problematic task.

different objects or between an object (i.e., signal or image) and a reference object (the target or prototype object).

The classification task is performed using the features or attributes distinctive of the object. The collection of the features that characterize the object of the classification is called *signature* or *footprint* of the considered object.

The aim of assigning an object to a class is an example of classification task. In the present case, it is possible to define a vector with specific features. We have

$$x = [x_1, x_2, \ldots, x_N] \tag{1}$$

where N is the number of features, and x represents the features. In the simple case where only two features are used, the classification task can graphically be represented as in Fig. 2. The main goal of a classifier is to partition the feature space in regions assigned to a classification class: the decision regions. In a multiple-class problem—as the discussed problem—several decision surfaces can be presented, and arbitrarily complex decision regions can be expected; the separation of the classes is achieved in essentially two ways: 1) *absolute separation* when each class can be separated from all the others; 2) *pairwise separation* when the classes can only be separated

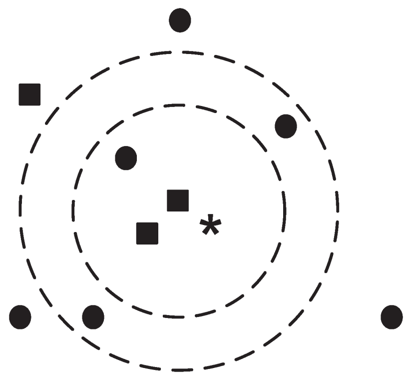

Fig. 3. Example of classification when a k-NN method is used. The symbols ■ and • indicate known patterns, while * is the pattern to be classified.

into pairs. For the sake of simplicity, we would like to use only a limited number of features; this task is obtained based on the previous knowledge of the object or problem. Therefore, if the acquired signals can be patterned, measurements, attributes, or primitives derived from the acquired signals can be useful features. The feature space is also called the *representation space*. The representation space has data-driven properties according to the defined similarity measure.

As the footprint of an object is generally more simple and compact than the object as a whole, processing operated in the features space is computationally less expensive.

The choice of the features can be based on the domain knowledge given by experts or can be made using some feature selection techniques. The deep knowledge of the mechanics and the physics of the particular machinery used may help in choosing well-performing features, but their use may not be generalized to the class of devices. Additionally, the features can be chosen as the parameters of an analytical model of the signal to be classified. In this case, the features (i.e., the parameters of the model) of each class may be estimated from the measured signals using a suitable function fitting procedure.

A brief overview concerning the most used classification algorithms is mandatory at this point. To classify an obtained feature, a possible way is to find the most similar footprint in the training set and, consequently, to find the class of that selected footprint. This kind of approach is named 1-nearest-neighbor (1-NN) classification. Moreover, it is possible to extend this method. In particular, it is possible to take into account the k most similar footprints and return the majority vote. This last approach is named as the k-nearest-neighbor (k-NN) classification method. These two methods are mainly based on the concept of majority vote of the neighbors. It is very important to discuss the value of the parameter k.

The schema in Fig. 3 can help in understanding this point. The method is based on fixing the number of points, i.e., k, that exist in a certain region centered on the feature space. With this aim, a region in the feature space centered on the feature to be classified has been grown, with a suitable metric, until k points are included inside the region. In Fig. 3, an example with two classes is represented in a 2-D feature space. Black square represents training examples of the first class, whereas the training examples of the second class are represented by a black circle. At least, the features to be classified are represented by an "$*$." The test examples could be classified either to the first class or to the second class. If a 3-NN method is used, the test examples are classified as belonging to the class of the black square features. On the contrary, if a 5-NN method is used, the test sample is classified as belonging to the black circle class. To classify a test feature, a distance metric would be used, i.e., a measuring rule in the feature space. The most popular and simplest choice is the Euclidian metrics, even if other metrics could be used, such as the squared Euclidian, or city block.

The choice of the k value may be critical. In fact, the parameter k grows with both the number of available pattern n and the dimension of the feature space d. A proposal was given in [10], where the method is used as a probability density function estimator. The k-NN classifier converges to the Bayesian classifier as k and n grow [11].

IV. Classification Tool Works as a Diagnostic Tool

In [1], Annoni *et al.* have just shown the strict correlation of the load current and instantaneous power signals to the water pressure values and their behaviors; this way, any operating condition of the monitored system appears on the main side as a variation in the motor current and, in the same way, in the instantaneous power [12], [13]. In Fig. 4, in fact, it is possible to note that the measured power profile shows a modulation strictly correlated to the motion of the piston; moreover, it is possible to observe that the shape of the power signal depends on the working condition. Signals obviously depend also on the water pressure level and on the changes of the machine status.

For this reason, an analysis of the variation of the profiles from the reference condition can be considered as a good support for monitoring the efficiency and effectiveness of the system.

In this paper, we explored a different method for characterizing the power signal with respect to the different working conditions. The proposed method is based on an analysis of the shape of the power signal in the frequency domain. For this scope, the discrete Fourier transform (DFT) of the power signal is processed to obtain the characterizing features. These features are used for configuring a classifier that will be used for recognizing if a new signal belongs to one of the classes considered during the configuration, or if it is representative of an unknown (faulty) situation.

Given a set of power signals $\{P_l\}$ and the class $\{C(P_l)\}$ to which they belong, the features f_i used for the analysis (i.e., the signals' footprint) are the first k coefficients of the DFT of each power signal, i.e.,

$$f_i = F(i), \qquad i = 1, \ldots, k \tag{2}$$

where F is the normalized DFT of the power signal P defined as

$$F = \|\mathrm{DFT}(P)\| \tag{3}$$

and k is a suitable value that depends on the sampling frequency and the duration of the signal acquisition.

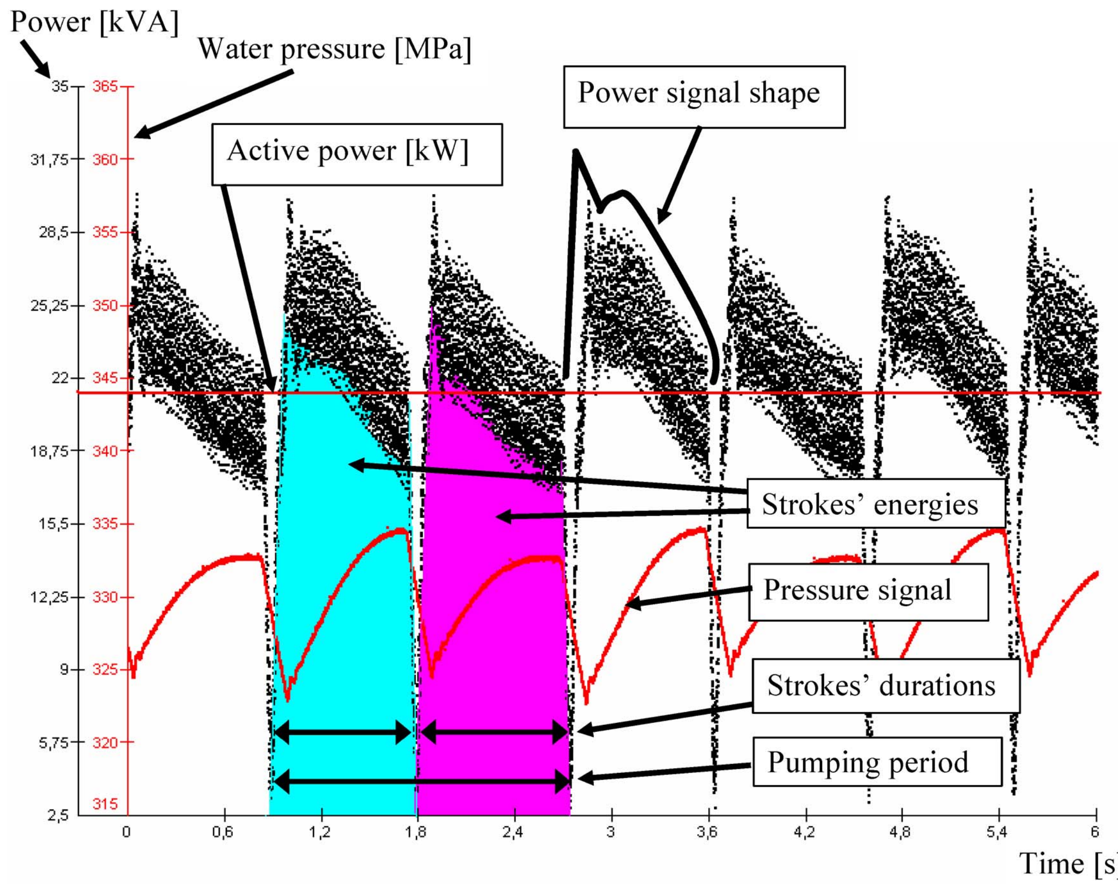

Fig. 4. Reference signal for a 0.30 mm nozzle at a nominal pressure of 330 MPa; sampling rate, 3.2 kHz; sampling period, 6 s.

The classifier will be composed by the description of those regions in the features space that contains the footprints the normal working condition signals. Those regions are described by means of the barycenter of the footprint and by the size of the region, which is described as the mean distance of the signals' footprints from the barycenter. Hence, the classifier is configured as follows. Given the signals belonging to the jth class, i.e., $D_j = \{P_l | C(P_l) = j\}$, the class footprint c_j is computed as the average of the footprints of the signals in D_j, i.e.,

$$c_j(i) = \frac{1}{n_j} \sum_{l=1}^{n_j} F_l(i), \qquad i = 1, \ldots, k \tag{4}$$

where n_j is the number of sample data for the jth class, i.e., $n_j = |D_j|$. Then, the size of the region r_j is estimated as the mean distance of the footprints of the jth class from c_j, i.e.,

$$r_j = \frac{1}{n_j} \sum_{l=1}^{n_j} |F_l - c_j|. \tag{5}$$

When a new power signal P_s is presented to the classifier, it is compared with all the class footprints by computing the distance of the footprint of P_s, i.e., f_s, from the class footprints, scaled by the radius of each class, as follows:

$$d_{sj} = \frac{|f_s - c_j|}{r_j}. \tag{6}$$

The normalized distance d_{sj} gives a measure of the confidence that the signal P_s belongs to class j. When d_{sj} is greater than unity, f_s tends to be farther from c_j than the footprints that belong to class j. Hence, a suitable threshold $d_{\max}$ can be set for detecting signals that belong to an unknown class. Otherwise, if $d_{sj} < d_{\max}$ for any j, P_s is assigned to the class that minimize the normalized distance, i.e.,

$$C(P_s) = \arg\min_j (d_{sj}). \tag{7}$$

V. Experimental Setup and Results

We applied the methodology described in Section IV on two data sets. Both the data sets have been acquired from the same AWJ system, but in different conditions: the second data set has been acquired after more than one year from the first one and after the AWJ system have been disassembled and moved in another location. Furthermore, the signals have been acquired with a different sampling frequency (3200 Hz for the first data set and 1600 for the second data set) and duration (19 200 samples for the first data set and 32 000 samples for the second data set). Each class of the data sets is identified by the triple composed of nozzle type "G" or "T," diameter of the orifice (20 and 30 for 0.20 and 0.30 mm, respectively), and working pressure (200 and 300 MPa). In Table I, the numerosity of each class for each data set has been reported. From each data set, five signals for each class have been randomly extracted for

TABLE I
NUMEROSITY OF THE CLASSES

Class	Dataset 1	Dataset 2
G-20-200	15	45
G-20-300	15	45
G-30-200	15	45
G-30-300	15	45
T-20-200	15	15
T-20-300	15	15
T-30-200	15	30
T-30-300	15	30

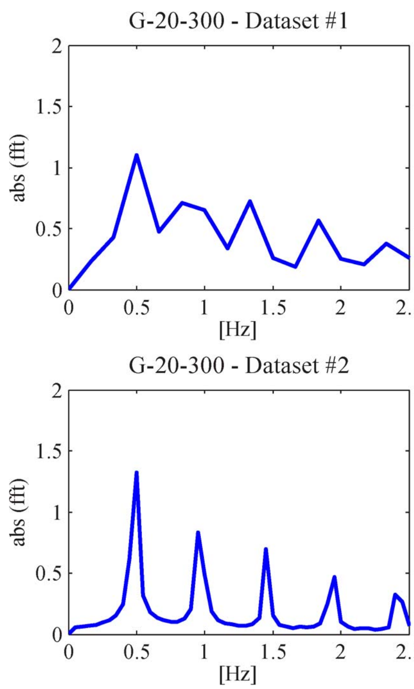

Fig. 5. Footprint of the class representing the G-20 (0.20 mm) nozzle working at 300 MPa.

composing the test data set, while the remaining signals have been used for configuring the classifiers.

The footprints of classes G-20-300, T-20-300, G-30-300, and T-30-300 are reported in Figs. 5–8. For each class, the DFTs of the power signal for the first and second data sets are reported in the upper and lower parts of the figure, respectively. As they correspond to the components that feature the lower frequency of the signal, they should carry noise-free information.

Observing these figures, two remarks arise. First, the effect of a different acquisition condition on the features vector can be noticed: the combination of different sampling frequencies and lengths of the acquisition makes the features of the second data set more defined than those of the first data set. Second, the similarity between the signals that refer to the same orifice diameter is apparent.

The length of the footprint k has been chosen (for each classifier), considering that the low-frequency content of the power signal should be related to the piston period, which is on the order of a few seconds, and the relative contribution of the DFT coefficient to the power of the signal. This consideration

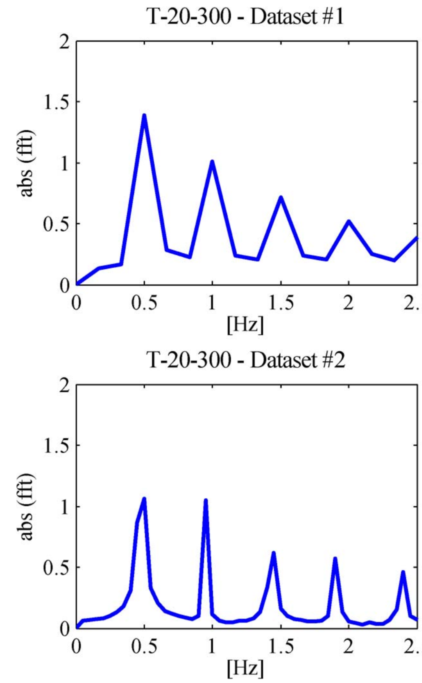

Fig. 6. Footprint of the class representing the T-20 (0.20 mm) nozzle working at 300 MPa.

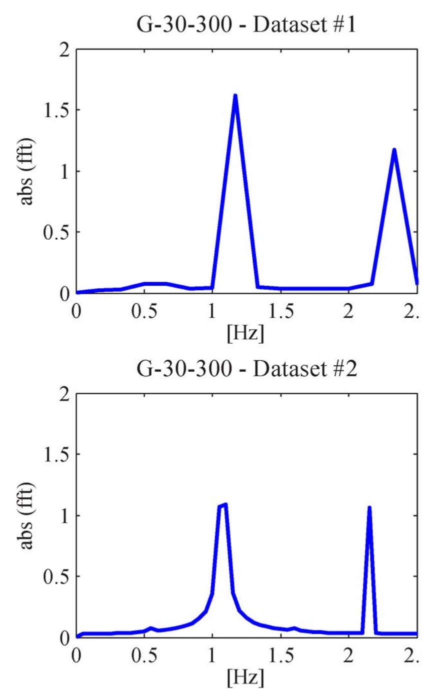

Fig. 7. Footprint of the class representing the G-30 (0.30 mm) nozzle working at 300 MPa.

leads to the choice of including enough coefficients in the footprint for covering the frequency components up to a few hertz as well as the first peaks of the DFT. The values of 16 and 50 have been chosen for k for the first and second classifiers, respectively (which correspond to the components up to 2.5 Hz). However, different values of k have been tested for both the classifiers, and the results are discussed later in this section.

To asses the ability of the classifiers, we challenged them on the data sets used for the configuration phase (configuration

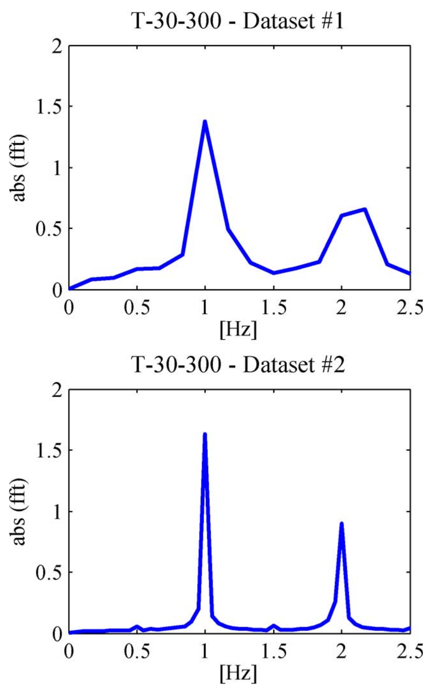

Fig. 8. Footprint of the class representing the T-30 (0.30 mm) nozzle working at 300 MPa.

TABLE II
CONFIGURATION AND TEST ERRORS WITH RESPECT TO THE NUMBER OF FEATURES USED IN THE CLASSIFIERS

#Classifier	k	**Config.**	**Test**
1	10	1.72%	2.97%
1	16	1.25%	1.50%
1	30	0.92%	1.95%
1	100	0.97%	1.65%
1	500	0.90%	2.15%
1	1000	0.92%	1.95%
1	5000	1.51%	2.67%
2	30	2.30%	2.72%
2	40	1.38%	1.17%
2	50	1.47%	1.13%
2	100	0.12%	0.30%
2	500	0%	0%
2	1000	0%	0%
2	5000	0%	0%

error) and on new power signals, which are sampled in different working conditions (test error).

Moreover, the performances of the classifiers have been compared with respect to those of a 1-NN classifier.

For evaluating the accuracy of the proposed approach, a cross validation procedure has been applied. Each experiment has been repeated 100 times, with a different test set for each trial, and the errors have been averaged on all the trials.

Results for different values of k have been reported in Table II. It can be noticed that for the second classifier, the use of a very high number of features allows obtaining a perfect classification, while for the first one, the use of a high number of features is of little or no advantage. Almost all the errors result in misclassification of the nozzle type.

TABLE III
PERFORMANCES OF NN-CLASSIFIERS

#Dataset	k-NN	Config.	Test
1	1	0%	1.63%
1	3	1.25%	2.0%
2	1	0%	0%
2	3	0%	0%

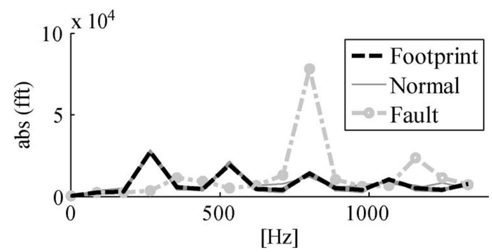

Fig. 9. Example of classification cases. Footprint is represented with the largest dashed line. An example of a fault case is represented by a dashed line, and nonfault cases are represented by solid lines. The nonfault case footprints are closer to the class footprint than the fault case.

In Table III, the performances of the nearest neighbor (NN) classifiers are reported.

The 1-NN classifier on data set 1 for $k = 16$ results in a configuration error of 0% and in a test error of 1.63%, while for data set 2, for $k = 50$, it does not make any error both in configuration and in test. It compares well with the proposed classifiers, as configuration and test errors of 1.25% and 1.5% resulted for the first data set and 1.47% and 1.13% for the second data set. It should be noticed that the performances deteriorate for 3-NN classifiers, which achieve 1.25% and 2.0% for the first data set.

The classification tools can be utilized even for fault recognition tasks. In fact, when the working condition is known, if the footprint of the correspondent power signal is not well positioned in the "*representation space*" with respect to the footprint of the same working condition, it automatically leads to considering the possibility of the presence of a faulty situation. These very important tasks can be demanded to an automatic procedure. In Fig. 9, the footprint of a typical malfunctioning case is compared to the footprint of the class to which, for the mounted nozzle and the working pressure, it should belong: it is evident that the distance of the fault case from the class footprint is greater than the mean distance of the footprint at normal working condition. This allows using, as a reference for fault diagnosis, the distribution of the distance of the footprint of signals acquired during normal working condition sessions from the footprint of the class to which they belong. Hence, during the configuration phase, the standard deviation of the distance of the footprint of the signals of each class from the class footprint can be computed and used to enrich the classification response with a measure of conformity to a standard working condition (e.g., see Fig. 10). It would be noted that the process mean always shifts to the right-hand side when the process is out of control, and this is well depicted. In fact, the distance of the actual footprint from the class

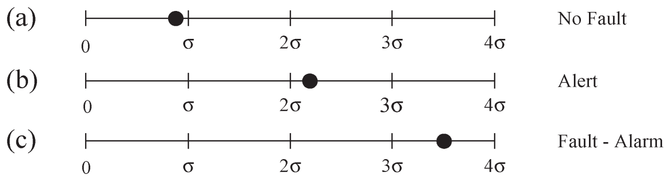

Fig. 10. Different working conditions may be recognized by observing the distance of the footprint of the actual power signal from the footprint of the considered class with respect to the distribution of the distance of the footprint in a normal working condition.

footprint can only be positive. This information can be used when a control chart for process control must be realized.

VI. Conclusion

This paper has the aim of showing that the electrical power signal is greatly influenced by the machinery setup and the working conditions. As the measurement of this entity is much more feasible than the direct measure of the other parameters that influence the working conditions of the system, the exploitation of its relation may lead to an automated method for revealing the machinery state and the presence of (an incoming) faulty behavior.

Although the proposed classifier underperforms the 1-NN classifier, it should be noticed that it is simpler, i.e., less computationally demanding. In addition, the NN classifier performances are greatly influenced by the number of neighbors. Furthermore, for the application described here, the faults occur very slowly, and the alarm may be arisen after several classification runs that robustly confirm or ignore the misclassification of a single sample.

This fact can be suitably exploited to increase the reliability and availability of the system, thanks to the defined diagnostic algorithm. The simplicity of the proposed approach leads to considering the possibility of realizing a low-cost real-time diagnostic system.

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