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A Tool for Working Condition and Nozzles Classification for Water Jet Systems

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Abstract – *In this paper, a technique for assessing both working and healthy condition of Water Jet System Nozzles is presented. The proposed classifier is based on the DFT of the electrical power signal. At this aim it will be shown that the electrical power signal support all necessary information to characterize the working condition of the system and to predict the presence of an incoming faulty behavior. For the sake of clearness, a brief description of a Water System is also presented.*

Keywords – *Water Jet Systems, classification, diagnosis.*

I. INTRODUCTION

Water Jet and Abrasive Water Jet Technology (WJ/AWJ) is often used in application fields where particular manufacturing operations on special material are required such as cutting hard to machine materials or carrying out operations such as turning and milling. In fact, the AWJ cutting process is a cold process as the water takes heat away from the interested area of the work piece. In every situation where it is necessary to carry out operation without damage the metallic material structure of the piece under work the aforementioned technology is very useful and in many case the use of it is mandatory.

The efficiency of the Water Jet system is influenced by the status of the water nozzle. This component plays an important role in the definition of the efficiency, measured as the ratio between the available fluid-dynamic power and the electric active power from the network. Starting from this consideration it would be noted that a monitoring activity devoted to evaluate the efficiency of the nozzle is mandatory to predict the efficiency of the AWJ system.

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

It would be shown that different power consumptions lead to differences, sometimes relatively large, in terms of cutting performance and also of operating costs of the system. Furthermore, it is shown that it is possible to extract information on the behavior of the AWJ system from of the power signal and this could allow to detect and foresee wrong operating conditions.

The aim of this paper is setting up a technique for extracting information from the electrical power signal about the working condition of the system. In particular, the interest is focused in both identifying the nozzle type and its working condition by means of an ad hoc developed signature for each nozzle in each working condition which allows the correct classification.

The availability of suitable signatures allows to build 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 further discussed in the following sections. In particular in Section II a brief description of a WJ/AWJ system has been presented, in Section III an introduction concerning Pattern Recognition has been presented. The classification tool is presented in Section IV while the Section V is devoted to report the experimental results.

II. PROPOSED SYSTEM ARCHITECTURE FOR CLASSIFICATION POURPOSE

The AWJ is characterized by phenomena belonging to different fields of physics and a brief discussion, using the schema in Fig. 1, could be useful to the reader. So, for the sake of clearness, the technical basis of the AWJ technology is briefly recalled here even if it was reported even in previous papers [1-12]. Considering a complete Water-jet Cutting System, electrical energy is provided at first to the 400 V - 50 Hz three-phase induction motor which pressurizes the oil by means of the radial pistons oil pump. The oil circuit pressure could reach a value of 20 MPa. The oil provides its hydraulic energy to water by means of the double-acting intensifier, as depicted in following Fig. 1. It would be noted that, in this application, the energy means of transport changes and, due to the increasing of 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 it flows through the orifice, the pressure energy changes into kinetic energy and a water jet is formed. Moreover, when abrasive water jet is considered, solid particles join the water jet inside the mixing chamber, being entrained by the air flow generated by the jet itself. In this particular case, the kinetic energy of abrasive particles is dramatically increased thanks 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 (water pressure, abrasive mass flow rate, abrasive granulometry, cutting head feed rate, standoff distance), as well as on the fluid-dynamic parameters, such as the orifice and focuser diameters and the mixing chamber geometry. Besides the aforementioned parameters, 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, granulometric distribution of the abrasive particles).

A DSP-based system has been designed, realized and tested in order to measure the interesting parameter of the complete water jet cutting system such as oil pressure, water pressure, and piston velocity and so on.

Furthermore, an Analog-to-Digital conversion board with simultaneous sampling up to 200 kHz sampling rate on a single channel with a 16-bit resolution has been utilized in order to acquire electrical motor signals.

Voltage and current transducers have been specially realized in order to:

1) adapt the signal levels to the ADC and,

2) ensure an adequate insulation level among channels and between the supply and measuring devices over a wide band.

III. PATTERN RECNOGNITION

Object recognition, description and classification are very important tasks for the daily life [7], [8], [9]. In particular, Pattern Recognition (PR) is the scientific discipline dealing with methods for both object description and object classification. Applications of Pattern Recognition Techniques are numerous and cover a broad scope of activities, ranging, for example, from satellite images analysis to biological signal classification, from traffic analysis and control to biometric recognition, from seismic analysis to surveillance systems. It is important to note that the patterns to be analyzed and recognized can be signals, images, plain tables of values or, finally, even an ad hoc developed signature evaluated starting from acquired signal from the field. Pattern recognition approaches are based on the notion of similarity: between two different object or between an object (*i.e.*, signal or image) and a reference object (the target or prototype object).

In the present work the Pattern Recognition activity is performed by means a pre-elaboration of the instantaneous power signal. A diagram of this signal is depicted in Fig. 2. Starting from these considerations, the classification task is performed using the features or attributes distinctive of the object, *i.e.* load current signal during a well specified working condition. 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 a typical example of a classification task. In particular, in the present case it is possible to define a vector with specific features, such as:

$$x = \begin{bmatrix} x_1 & x_2 & \dots & x_N \end{bmatrix} \quad (1)$$

with N features named x. A simple example could be useful

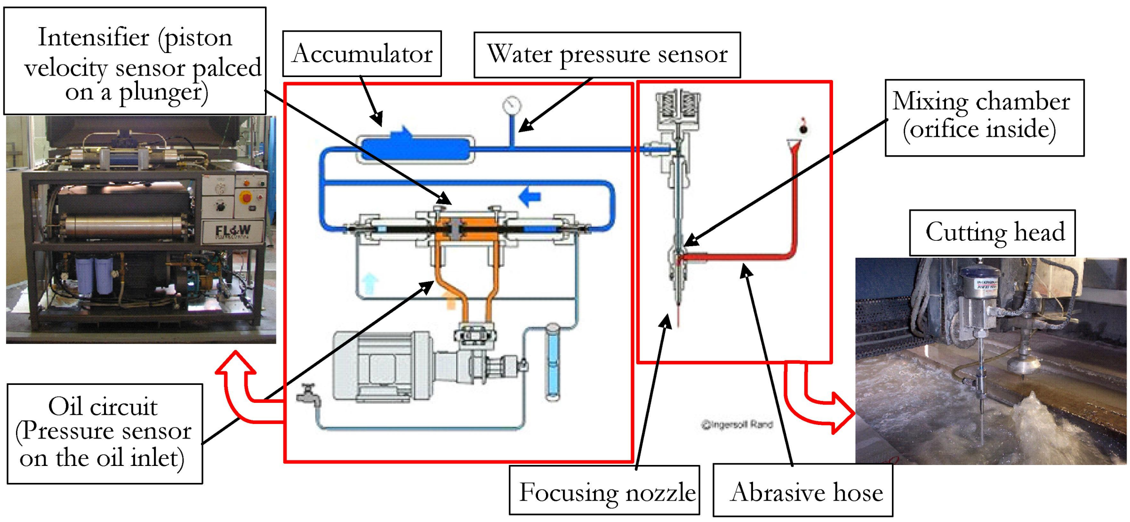

Fig. 1. Main components of the water jet cutting system (scheme in the middle by Ingersoll Rand; pictures by Politecnico di Milano).

to make this concept clear. For example, if only two features are used during the classification task, the situation can be represented on a plane as shown in Fig. 3. In general, a feature vector is a point in the feature space.

The main goal of a classifier is to divide the feature space in regions assigned to a classification classes: the decision regions. In a multiple class problem – as the discussed in the present work – several decision surfaces can be present and arbitrarily complex decision regions can be expected. In this situation it is not possible to use a simple graphical representation due to the fact that a multidimensional space would be necessary. The configuration of the classifier has to enforce the separation of the classes. It can be obtained in essentially two ways: (1) absolute separation: in this case the features are selected in such a way that each class can be separated from all the others, such as reported in Fig. 4 for a simple two dimensional example; (2) pair wise separation: when the features are selected considering the separation of a pair of classes. This last approach can be used to refine an already configured classifier which presents an overlapping pair of classes, *e.g.*, as the situation represented in Fig. 5.

As the footprint of an object is generally more simple and compact than the object itself, processing in the features space is computationally less expensive. Hence, a feature extraction procedure has to be operated on the considered objects. This task is carried out exploiting the previous knowledge of the object or problem. Patterns, 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.

The choice of the features can be based on the domain knowledge given by experts or can be made using some feature selection technique. The deep knowledge of the mechanics and the physics of the particular machinery used may help to choose well performing features, but their use may not be generalized to the class of devices.

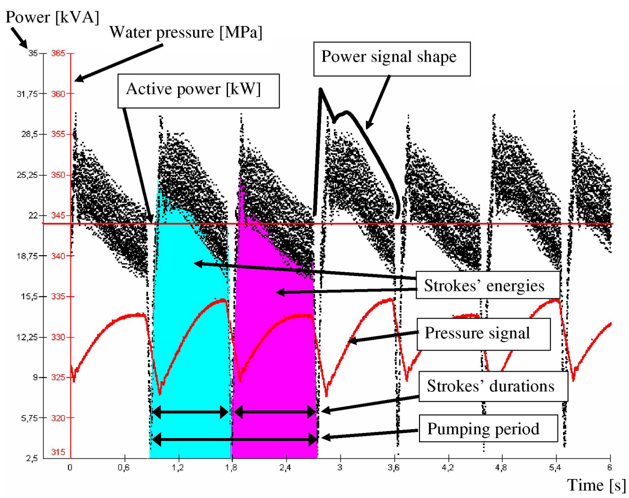

Fig. 2. Reference signals for a specific nozzle; sampling rate: 3.2 kHz; sampling period: 6 s.

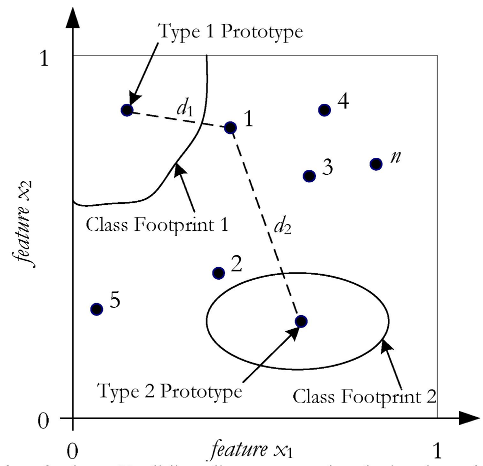

Fig. 3. $f_1 - f_2$ plane. Euclidian distance are also depicted on the plane. Classification of object 1 or 2 is a simple task. However, classification of other points (3, 4, 5 and n for example) is a more problematic task.

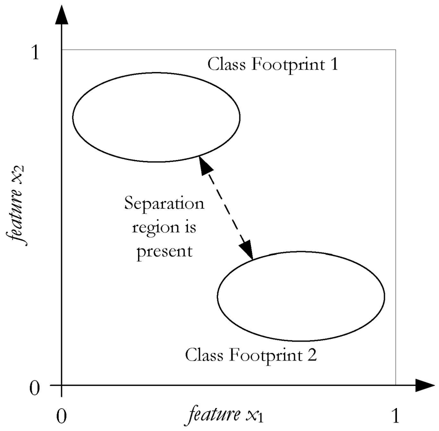

Fig. 4. Absolute separation for a two dimensional feature space.

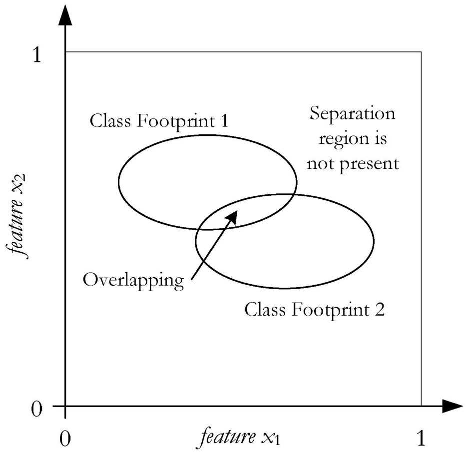

Fig. 5. Pair wise separation: the overlapping classes have to be separated.

IV. CLASSIFICATION AND DIAGNOSTIC TOOL

In [1] the authors have just shown the strict correlation of the load current and instantaneous power signals to the water pressure values and their behaviors; in this way any operating conditions 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 (see the aforementioned Fig. 2). 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 shapes of the power signal depend by the working condition. Signals obviously depend also on the water pressure level and on the changes of machine status.

For this reason, an analysis of the variation of the profiles from the reference condition of the instantaneous power signal can be considered, and it has been so considered in that paper, as a good support for monitoring the efficiency and effectiveness of the system.

In the present work 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 Discrete Fourier Transform (DFT) of the power signal. Hence, the characterizing features of the power signal are obtained by a processing operated in the frequency domain. The features, f_i used for the analysis are the first k coefficients of the DFT of the power signal:

$$f_i = F(i), \quad i = 1, \dots, k \tag{2}$$

where

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

is the normalized DFT of the instantaneous power signal, P (an example of the Power signal is shown in the previous Fig. 2). For this application, we chose $k = 15$, as it allows to use the most significant coefficients (the performance of the system does not change for a greater value of k).

For each class, j, identified by the type of orifice, its diameter and the working pressure, we compute the class footprint, $f(j)$, as the average of the feature vectors, F_l, (computed as in (3)) of the signals belonging to the class, $\{P_l\}$:

$$f_i(j) = \frac{1}{n_j} \sum_{l=1}^{n_j} F_l(i), \quad i = 1, \dots, k \tag{4}$$

where n_j is the number of sample data for the j-th class,

$$n_j = |\{P_l\}| \tag{5}$$

The ensemble of the class footprints constitutes an Euclidean classifier: when a new signal has to be classified, its footprint is compared to each class footprint and the new signal will be assigned to the class whose footprint will result the closer to the new signal footprint. In particular, the classifier task is realized using a minimum distance criterion. The utilized classifier is a linear task and it can be therefore simply implemented on simple industrial microcontroller for example. This is mandatory incase of application in industrial environment where simplicity and low cost are very important, even if in the present case this constrain are not mandatory.

Two kind of classification error may, obviously, occur in this activity:

Type* 1 *error: when a signal belonging to a given class, i, has a footprint more similar to the footprint of a different class, j;

Type* 2 *error: when a signal belongs to an unknown class.

The first type of misclassification occurs when the classes are overlapped in the features space, and can be usually avoided using more features (or more meaningful features). This statement do not means that in any case it is possible to obtain classes with a separation region. The second type of misclassification is harder to cope with. A common approach is to exploit the data used for the configuration of the classifier for obtaining a more accurate description of the region of the space occupied by each class. We chose to store in the classifier not only the average of the signals' footprint, F_l, but also the mean and the standard deviation of the distance of the class footprint from the signals footprint, δ_l and σ_l, respectively. This allows to estimate the region occupied by the l-th class as the (hyper)sphere centred in F_l having the radius equal to $\delta_l + \lambda\sigma_l$ (for an appropriate value of λ); when a footprint will result external to each of these sphere, the corresponding signal will be classified as unknown.

Observing the signal which refers to the same orifice diameter (Fig. 6), it is apparent that they share the same pattern warped by an unknown scaling operator that depend on the pressure. In the frequency domain, this behaviour results essentially in a scaling of the frequency components, and hence, in the scaling of the features position. Hence, it is possible to devise only a class for each orifice, whose footprint will be constituted by a surface, instead of a vector. Such feature surface can be constructed by distributing the feature signals along the pressure axis, as reported in Fig. 7.a, and properly interpolating this signal. The simpler feature surface can be obtained by linearly interpolating the class signatures (Fig. 7.b and Fig. 7.c). The points belonging to the resulting feature surface can be described as $S_i(p)$, where the index i refers to the DTF coefficient ($i = 1, \dots, k$), while p is the value of the working the pressure.

For matching a sample, s, (which is a polyline) with the classifier surface, $S_i(p)$, (which is a linear mesh) the sample can be translated over the surface along the pressure axis and the distance of the sample from the surface can be defined as the sum of the distance of the vertices from the surface:

$$p_{\text{best}} = \min_p (s - S_i(p))^2 \tag{6}$$

This formulation allows to compute efficiently the best matching pressure, by decomposing the optimization problem in (6) in the linear optimization problems given by considering the linear interpolation of two subsequent signature. In fact, given two signatures a and b, referring to the working pressure p_a and p_b, respectively, and an unknown signal feature vector, s, the pressure that optimize (6), p_{best}, is:

$$p_{\text{best}} = \frac{\sum_i d_i (s_i - a_i) + d_i^2 p_a}{\sum_i d_i^2} \tag{7}$$

where

$$d_i = \frac{(b_i - a_i)}{(p_b - p_a)} \tag{8}$$

It would be note that the feature surface allows to classify a signal for a known nozzle for an unknown pressure. This feature is very important. In fact, even if a deep experimental activity is mandatory, it is not possible to acquire data from all possible values of pressure. The typical situation, in industrial application, is the availability of data at 5-10 different working pressure, including the max pressure level.

The ability of the classifier to interpolate the non available situation is mandatory and it is verified in different case of studies as discussed in the following Section V.

V. EXPERIMENTAL RESULTS

The experimental results are obtained considering many different case of study. For sake of simplicity, in this paper a reduced set of tests are reported.

We tested the two kind of classifier described above (Section IV): the single signature (with threshold) classifier and the surface classifier. The dataset available for configuring the classifiers is composed of 130 samples of the power signal in 10 working conditions: nozzle with an orifice of two different diameters (0.20 mm and 0.30 mm) for five different values of working pressure (100, 150, 200, 250, and 300 MPa).

The test set has been composed by 2 sample for each of the working conditions. Besides, to test the ability of the single signature classifier to catch unknown working conditions, we added six samples of an orifice made by a different producer, operating in similar working conditions (specifically, 0.20 mm/150 MPa, 0.20 mm/250 MPa, 0.30 mm/150 MPa). For the estimation of the hypersphere radius we set $\lambda = 1$.

The configuration error (*i.e.*, the measure of the misclassification occurred for the configuration dataset) has been of about 0.77% (1/130), stating that a good separation of the classes has been achieved. Furthermore, all the unknown data were correctly classified as unknown, while all other test samples error has been correctly classified (0% test error).

To test the ability of the surface classifier to recognize patterns that belong to the same orifice, but that operate in an unknown working condition, we used, for each orifice diameter, only the data related to the 100, 200, and 300 MPa. Hence, the surface classifier is constituted by two surfaces, similar to the one reported in Fig. 7.b. The test set has been composed by 20 samples, 2 for each working condition (including the intermediate pressures, 150 and 250 MPa).

Only 1 of 20 test samples were misclassified (wrong diameter, although the relative error in the pressure estimation has been of 3.57%). The mean absolute error on the pressure estimation has been 8.81 MPa (with a standard deviation of 8.67 MPa). Overall, the relative error in the pressure estimation for the samples of working conditions directly used in the classifier configuration (*i.e.*, 200, and 300 MPa) has been 2.75%, while for the intermediate working condition the mean relative error has been 9.79% (the only misclassification belongs to this subset). This fact may indicate that the linear interpolation of the class signatures does not reliably describe the real features surface.

VI. CONCLUSIONS

In the present work we had shown 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 which 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.

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 lead to consider the possibility of realizing a low cost real time diagnostic system. Further develop in this direction are now in progress.

The surface classifier may be improved by using a more complex surface approximating technique.

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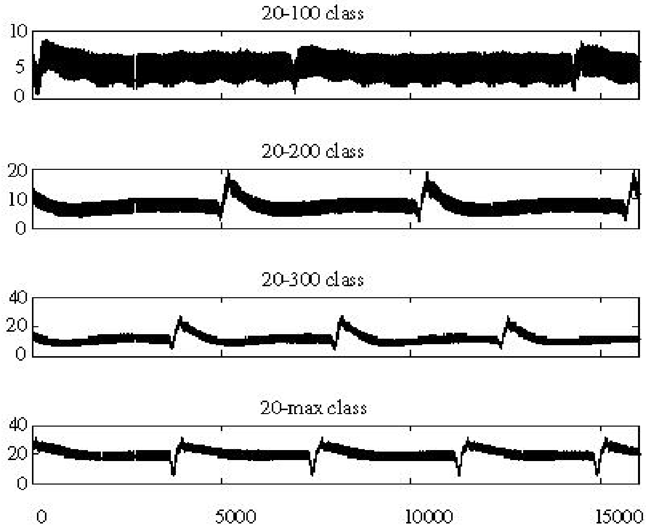
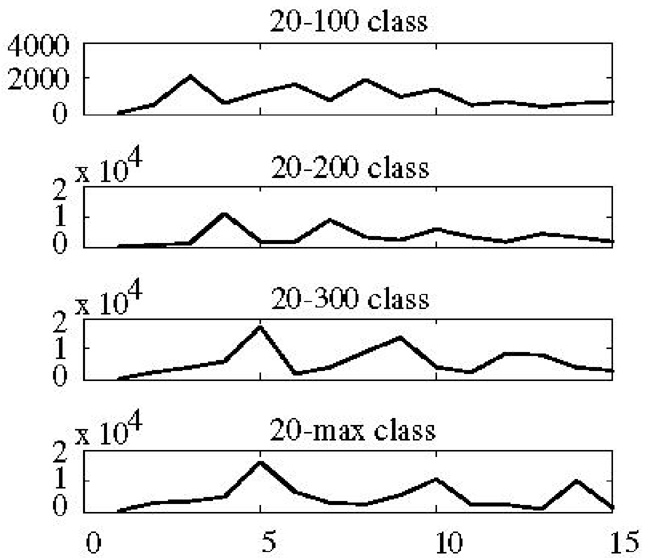
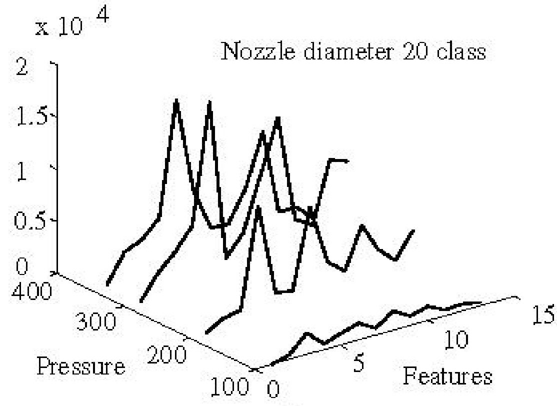


(a)



(b)

Fig. 6. The samples (a) and the footprints (b) of the same nozzle at different pressures.



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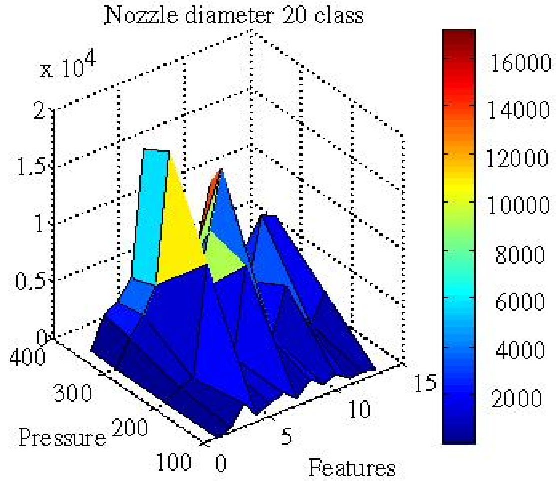

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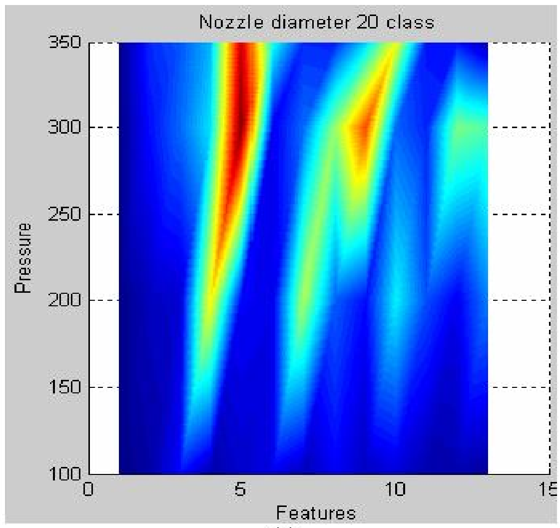

(c)

Fig. 7. The footprints of the same nozzle (see Fig. 6) at different pressures may be used to build a pressure-independent footprint of the nozzle.