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EMBEDDED DATA ACQUISITION SYSTEM FOR PROCESS SIGNATURE SURVEY

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Abstract: The advancement of technology and the needs imposed by the market, such as high surface quality and reduction of manufacturing costs, have made machine tools the focus of numerous researches, aimed at improving their performance in different industrial processes. Some of these researches have as objective the instrumentation of the machine, aiming at the monitoring of some variables related to the machining process. To carry out such monitoring, systems with sensors are used that allow the measurement of physical quantities that are closely linked to the cutting parameters (feed, cutting speed and cutting depth). These parameters are of fundamental importance for the process and help in the good machinability of the materials, an error in the configuration of these parameters, before or during the process, can cause wear or even breakage of the tool. The main quantities used in monitoring machine tools are mechanical vibration (correlated with the rotation of the workpiece and the movement and wear of the tool), temperature (which varies mainly with the plastic deformation at the workpiece-tool interface and the friction at the workpiece-tool and chip-tool interfaces) and sound vibration (related to stiffness and friction between materials). This article presents the development of a system that monitors acceleration, temperature, and sound emitted during an external turning process, using an embedded system (data acquisition and processing boards) with low cost and high computational power. To determine the process signature that relates temperature, vibration and audio to the machined material and to the cutting parameters (feed and depth of cut), an Artificial Neural Network (ANN) was used, which obtained an accuracy rate of approximately 80%, indicating that the monitoring system is capable of generating data that allows the determination of the process signature.
Keywords: Turning, Monitoring System, Instrumentation, Process Signature.

INTRODUCTION

Industry plays a leading role in a country's economy, which implies that manufacturing is related to economic development [1]. This scenario can be noticed in both developed and developing countries[2].

Therefore, numerous researches have been developed in recent years to change the traditional concept of manufacturing to an automatic and intelligent profile, which gave rise to the so-called Industry 4.0. In the traditional concept of manufacturing, in the manufacturing process an operator inspects the tool, the part and the cutting parameters in order to perform a satisfactory machining. Along these lines, Industry 4.0 proposes the use of a specific monitoring system to carry out this inspection [3].

Along with this, from data collected by monitoring systems, the concept of process signatures began to emerge in the literature, which are behavior patterns of physical quantities that represent the interaction between the material and the process, from a chemical and physical point of view [4].

One of the main challenges of implementing a monitoring system in a manufacturing process is the instrumentation of the machine tool, so that the measured variables are correlated with the material and the process to allow a process signature to be collected. Thus, the present work aims to develop an embedded and modular monitoring system that allows parallel acquisition of sensor data during an external turning operation in order to obtain a process signature.

LITERATURE REVISION

As noted in [5], a monitoring system for the manufacturing process can be built as shown in Fig.1. In a manufacturing process, sensors are allocated in the machine tool to measure physical quantities correlated with the process, finally, the measured signal is conditioned and digitized by an acquisition system. The advantage of using a monitoring system in machining processes is that they generate economy and practicality, since it allows the detection of tool wear, part roughness and other parameters related to the process for the production of a part [6].

QUANTITIES FOR MONITORING MACHINE TOOLS

The most used quantity for monitoring manufacturing processes is vibration, in machining processes, this variable arises due to the interaction in the machine-fixation-part-tool system and directly influences the surface quality of the part, tool wear and machine robustness. There are two types of vibrations in the machining process [7]: forced generated by the workpiece and tool contact and self-excited generated by the material removal rate.

Several works have been carried out aiming to correlate the vibration with: the flank wear of the tool, for example, [8] which determines the instants in which the tool has a wear transition; cutting parameters such as [9] which shows that the maximum magnitude in frequency of the acceleration signal is a measure sensitive to changes in speed and depth of cut.

Temperature is another physical quantity that is much studied in manufacturing processes, when referring to turning, a lot of energy is spent to remove material by plastic deformation and most of this energy is transformed into heat. The dissipation of this heat occurs through the workpiece, the chip and the tool [10].

Among the applications for temperature monitoring, we can mention: determining the average roughness (Ra) as, for example, in [11] shows that the increase in temperature due to the shear parameters generates an increase in Ra; analyzing the tool wear, for example, in [12] it is observed that the cutting speed and the feed per tooth have a greater influence on the tool temperature, while the depth of cut has a lesser influence; optimizing cutting parameters, in order to minimize the average cutting temperature, in [13] notices that the depth of cut affects the average cutting temperature more, while the feed and cutting speed influence less.

Sound vibration is another quantity researched in works related to manufacturing, as the machining processes, in general, they produce sound due to friction in the workpiece/tool contact zone. One of the applications for this quantity is to determine the relationship between the roughness of the part and the cutting parameters, in [14] comes to the conclusion that the feed is the parameter that has the greatest relationship with the roughness of the piece when analyzing the frequency of sound vibration. Another area of interest is with regard to tool wear, in [15] shows that it is possible to determine tool flank wear ranges according to the sound vibration emitted during machining, obtaining a hit rate above 95%.

PROCESS SIGNATURES

The interaction between the machine, tool and material generates response patterns of some physical quantities given a certain cutting condition, this is the so-called process signature. Such standards can be correlated to several process characteristics, such as surface integrity, this parameter is extremely important for the industry, as it has a direct influence on the quality of the final product.

In [4], he presents a methodology of process signatures so that, based on the conditions of the final surface integrity of the part, it is possible to adjust the cutting parameters during the manufacturing process. Based on the relationship between the internal loads in the material and the physical changes generated in it, process signatures are created to correlate cutting conditions and parameters with surface quality.

Another factor that generates patterns when analyzing some physical quantities is the wear of the tool, therefore, there are many works in the area of monitoring the state of the tool and each sensor generates a different process signature.

In [16], he proposes to use several sensors to monitor the tool, aiming to correlate the response of the sensors with their state. Based on the data obtained, it is claimed to be possible to determine a signature for the tool breakage, using both an accelerometer and an acoustic emission sensor.

In [17], tool wear and cutting parameters are related from the sound generated during the manufacturing process. The variable parameters under study are feed and cutting speed, while depth of cut is a fixed parameter. The magnitude of a given frequency is compared with the noise generated by the motor, due to the different stages of tool wear. From the data obtained, a process signature is identified based on a spectrogram.

In [18], tool wear in the gear manufacturing process is monitored through the acoustic emission signal. To perform the classification, the fusion of responses from different classifiers is used. With data in the frequency domain, classifiers were used to determine tool wear (Hidden Markov Model, Bayesian Inference, Gaussian Mixture and *K-means*) and to improve the accuracy of the model, the fusion of the classifiers was proposed.

METHODOLOGY

The methodology used in this research can be seen in Fig. 2. The first stage consists in the development of hardware and software for data acquisition. Then, data collection takes place on the working machine tool. In pose of the data, the third step is carried out, which consists of processing the data acquired according to [19]. From the processed data, an exploratory analysis is carried out in search of insights to choose the machine learning algorithm and, finally, generates a solution that identifies the process signature.

MACHINE TOOL INSTRUMENTATION

The temperature sensor, type K thermocouple, was fixed on the secondary cutting surface, there is a distance of 4 mm from the cutting edge, as shown in Fig. 3.

The vibration sensor, 780B, manufactured by the company *Wilcoxon Research*, the entire signal conditioning step of this sensor is in [19]. To avoid contact between the transducer and the chip, it was decided to perform the measurement on the Y axis, which is parallel to the tool feed, as can be seen in Fig. 4.

To measure the sound vibration, an electret microphone was used, the entire signal conditioning step of this sensor is in [19]. The microphone was installed on the tool holder pointing towards the cutting region, there is a distance of approximately 800 mm from the main cutting edge, as can be seen in Fig. 5.

DATA ACQUISITION SYSTEM

For data acquisition, embedded platforms Tiva C Connected LaunchPad were used, developed by the company *Texas Instruments*, for the sensor layer and a Raspberry Pi 2 model B board for the master layer The representation of the developed system can be seen in Fig. 6, the sensor layer is modular, making it possible to add new devices to the LAN, being responsible only for capturing and sending data. The master layer is responsible for identifying the sensors that are available

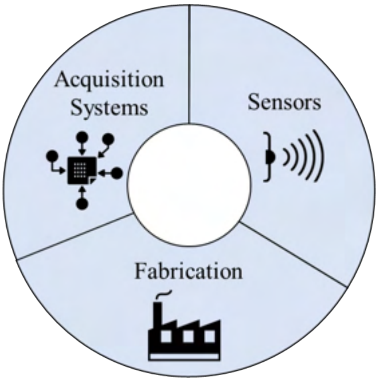

Figure 1: Representation of a monitoring system.

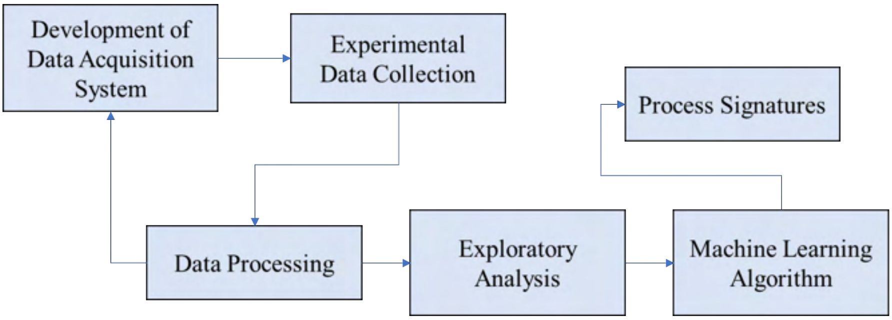

Figura 2. Metodologia.

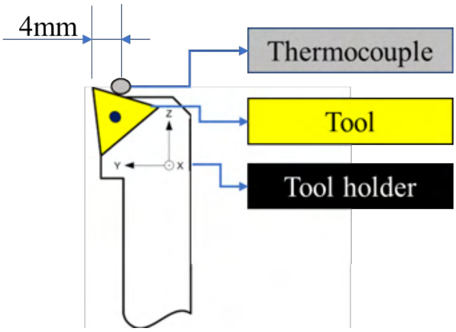

Figura 3. Fixação do Termopar.

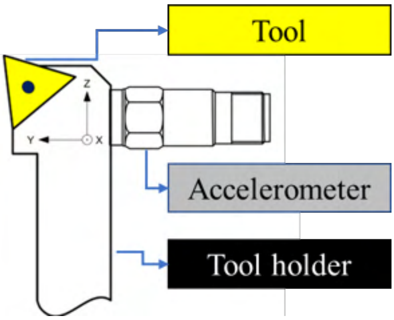

Figure 4. Fixation of the Accelerometer.

on the LAN and managing the acquisition and collection of data.

The time diagram representation of the data acquisition system can be seen in Fig. 7. The master layer enables two periods, the acquisition period, in which the sensors collect data in parallel for a fixed time of 5 seconds and, at the end of this period, the transmission period begins, which serializes the collection of the data of each module in the sensor layer.

SETUP EXPERIMENTAL

To carry out the experiments, the ROMI Centur 30D machine tool was used, the materials machined were 25.4 mm diameter cylinders of aluminum and SAE 1020 steel and the tool to perform the machining is TNMG160408R-C NS530 from the manufacturer Tungaloy . The cutting parameters were: cutting speed of 200 m/min; cutting depth of 0.30 mm (finish) and 1.00 mm (rough); feed rate of 0.10 mm/rev (finish) and 0.25 mm/rev (rough).

RESULTS

For the representation of the machining conditions, a pattern was used in the graphics, such consideration can be seen in Tab. 1. The first and second columns represent the ID and symbol used in the charts; the third column indicates the machined material; the fourth column represents the depth of cut (*ap*) and the advance (*f*) of the tool used during the experiment.

EXPLORATORY ANALYSIS

For the temperature magnitude, the difference between the measured temperature and the ambient temperature, obtained by a thermometer inside the room, was calculated. In Fig. 9 shows the distribution of temperature variation on the vertical axis and, on the horizontal axis, the experiments are numbered according to the data in Tab.1.

It is noted that the finishing conditions (Experiment 5 for aluminum and Experiment 6 for steel) are the ones with the smallest temperature variations. On the other hand, the greatest temperature variations occurred in the roughing condition (Experiment 1 for aluminum and Experiment 2 for steel), something logical to think about due to the fact that in roughing there is a greater removal of material, increasing the specific energy and, consequently, generating more heat. Furthermore, within the two classes, it is noted that aluminum (experiments 1 and 5) generated a smaller temperature variation when compared to the temperature generated by steel (experiments 2 and 6).

For the acceleration magnitude, the Root Mean Square (RMS) was calculated. In Fig. 10 shows the RMS distribution of the acceleration signal on the vertical axis and, on the horizontal axis, the experiments are numbered according to the data in Tab. 1.

It can be seen that rough machining (Experiment 1 for aluminum and Experiment 2 for steel) caused greater acceleration amplitudes than the finish machining situation (Experiment 5 for aluminum and Experiment 6 for steel), making consideration of comparing the same material. This is intuitive, as the efforts caused during a roughing operation are greater than those required for finishing, due to the rigidity of the tool holder. Another interesting factor that can be raised is that in the roughing and finishing conditions, the average of the RMS value of the experiments for the aluminum material is higher, considering the same situation, than for the steel. Therefore, for this frequency range analyzed, aluminum absorbs vibration better.

For the audio magnitude, the Root Mean Square (RMS) was calculated. In Fig. 11 shows the distribution of the RMS of the audio signal

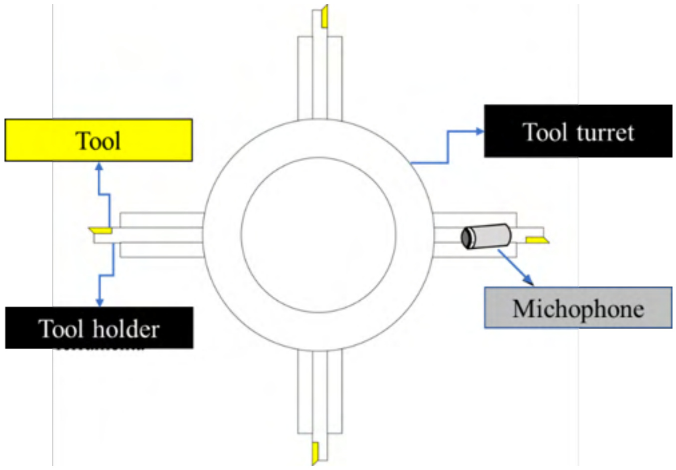

Figura 5. Fixação do microfone.

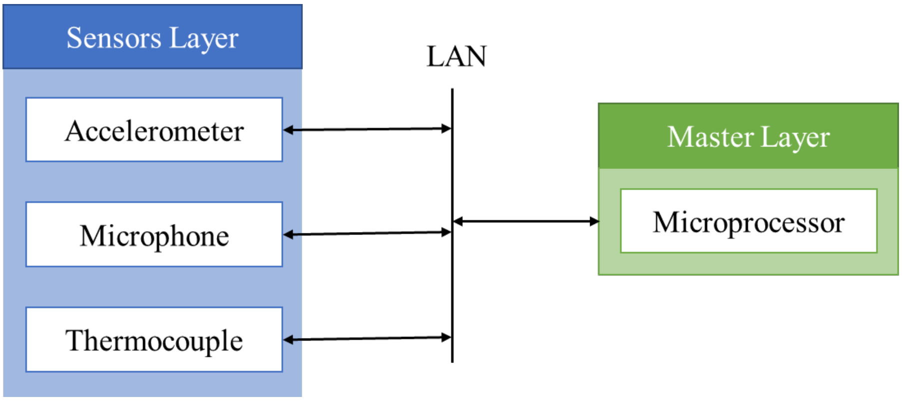

Figure 6. Data Acquisition System.

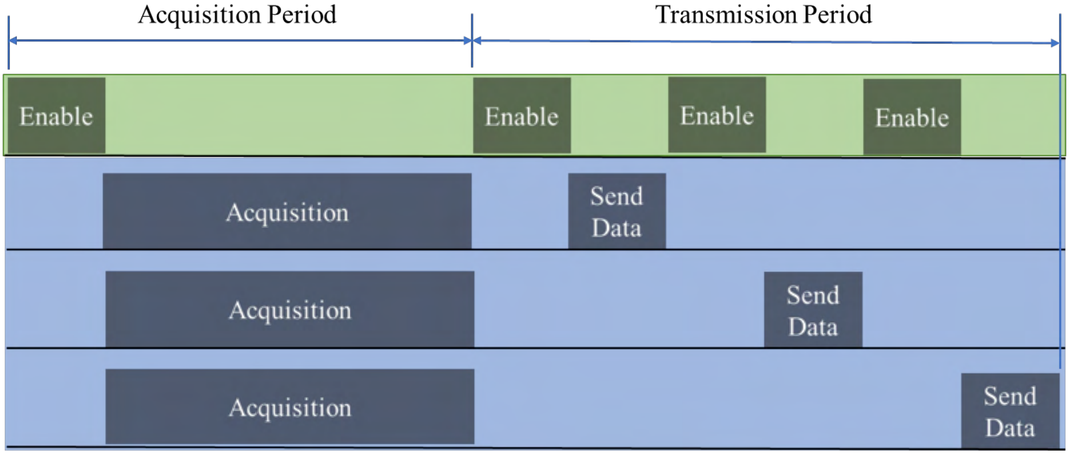

Figure 7. Acquisition system timing diagram.

ID	Symbol	Material	Cutting Parameters
1	○	Aluminum	ap = 1,00 mm f = 0,25 mm/rev
2	△	Steel	ap = 1,00 mm f = 0,25 mm/rev
3	+	Steel	ap = 0,30 mm f = 0,25 mm/rev
4	×	Aluminum	ap = 0,30 mm f = 0,25 mm/rev
5	□	Aluminum	ap = 0,30 mm f = 0,10 mm/rev
6	◇	Steel	ap = 0,30 mm f = 0,10 mm/rev
7	☆	Steel	ap = 1,00 mm f = 0,10 mm/rev
8	✡	Aluminum	ap = 1,00 mm f = 0,10 mm/rev

Tabela 1. Representação e dados utilizados nos experimentos.

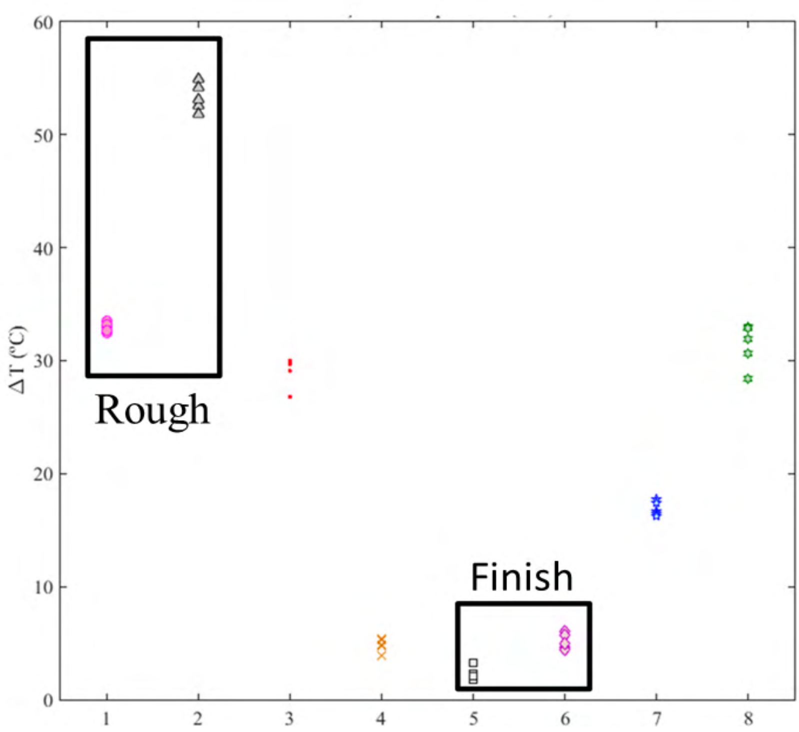

Figure 9. Temperature variation data for the different experiments.

on the vertical axis and, on the horizontal axis, the experiments are numbered according to the data in Tab. 1.

When analyzing the data distribution, it is observed that, for the steel material, the rough machining (experiment 2) caused an RMS of sound vibrations of greater amplitude than the finishing machining (experiment 6). On the other hand, looking at the aluminum material, the situation differed, as the finishing situation (experiment 5) generated a higher RMS than for roughing (experiment 1). Another analysis that can be done is that the data for the experiments whose machined material is aluminum (experiments 1, 4, 5 and 8) was higher than for the steel material (experiments 2, 3, 6 and 7).

MACHINE LEARNING ALGORITHM

To extract the process signature, the classification algorithm based on *Artificial Neural Network* (ANN), cuja arquitetura é denominada *Radial Basis Function* (RBF), The topology used can be seen in Fig. 12. This denomination is due to the fact that the activation function of the neurons of the first layer is of radial basis, as, for example, a Gaussian function, used in this work. For the 908 external turning samples, the dataset was separated into 75% for training and 25% for testing, using the cross-validation technique *k-fol*d with 5 iterations.

The weight matrix between the input layer and the first layer can be seen in Tab. 3. Such weights indicate the cluster position obtained by the *k-means* algorithm for the data under analysis. Note that the weights related to the third entry (third column of the table) have greater variation, which indicates that the third entry (temperature variation) is a variable with a high capacity for data separation, as well as the second entry (audio).

The weight matrix between the first layer and the output layer can be seen in Tab. 4. The activation function of the intermediate layer was the hyperbolic tangent (tanh) and the softmax function was used in the output layer to identify the probability of occurrence of each of the classes under analysis.

The confusion matrix that relates the observed variable with the predicted one for the model in question is presented in Tab. 5. It is observed that the model had difficulty with experiment 8, which had a low accuracy, less than 30%. The model had a total accuracy of 79.74% and the precision between classes ranged from 70% to 100%.

CONCLUSIONS

In this article, a modular monitoring system was developed that allows the parallel acquisition of data during a manufacturing process. With the data acquired from this system, a classification algorithm based on ANN was proposed to classify machined material and cutting parameters: feed and depth of cut.

The master layer performed well in terms of speed, with three devices in the sensor layer, but adding new devices can cause the system to slow down.

ANN obtained a hit rate of 79.74%, showing a good performance for the prediction step, proving that this technique can generate process signature. There is a possibility that, by collecting more data, the accuracy of the model can be increased.

Most of the classification algorithm errors occurred due to the dispersion of the tool acceleration data. Therefore, it is necessary to investigate the behavior of this variable when changing the location of the accelerometer, making the measurement more sensitive to the parameters analyzed.

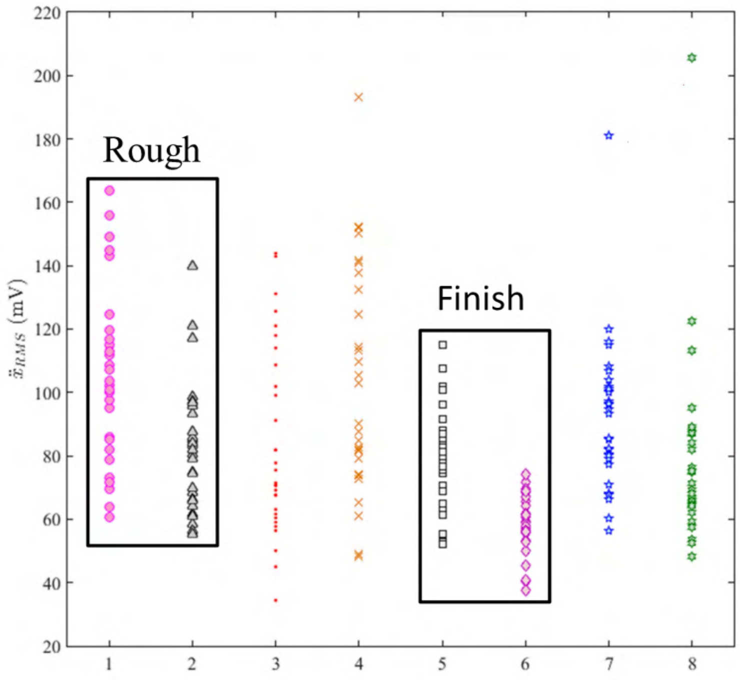

Figure 10. RMS value of the acceleration data for the different experiments.

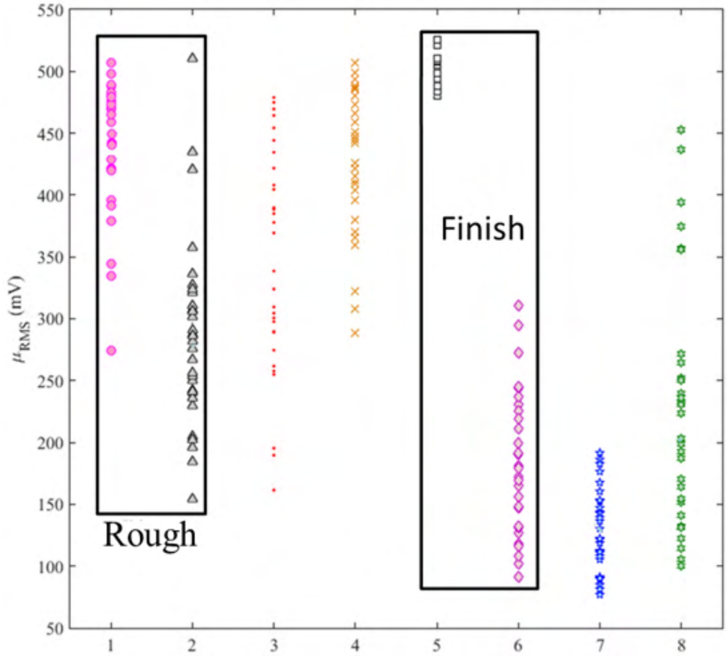

Figure 11. RMS value of the audio data for the different experiments.

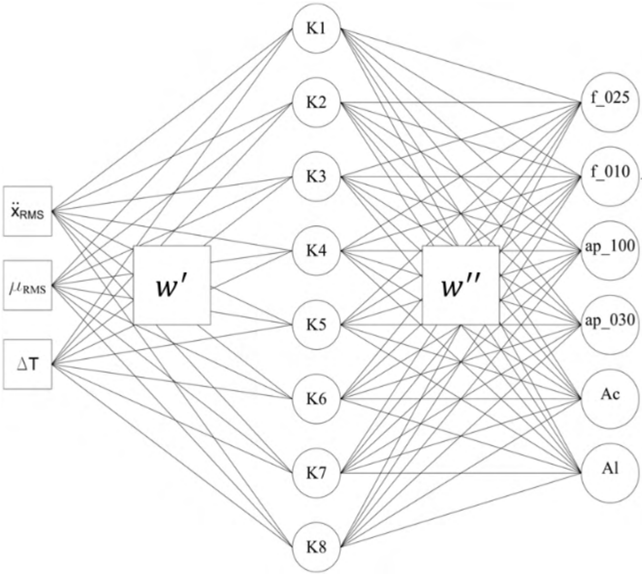

Figure 12. RBF used for classification.

w'	1	2	3
1	107,8	440,1	32,9
2	78,6	279,4	53,3
3	85,5	350,1	29,1
4	102,3	423,2	4,87
5	80,9	500,2	2,2
6	59,0	186,5	5,2
7	88,7	126,9	16,9
8	72,1	205,5	31,7

Table 3. Matrix of weights between the input layer and the first layer.

w″	1	2	3	4	5	6
α	-0,0	0,1	0,2	-0,2	0,0	0,5
1	5,7	-6,0	11,1	-11,1	7,6	-7,6
2	-0,0	-0,3	-4,8	4,8	-3,1	3,2
3	-3,5	3,6	2,8	-2,8	5,8	-5,8
4	4,3	-4,1	-12,0	11	-13,2	13.2
5	-14,6	14,9	-6,8	6,8	-4,7	4,6
6	-13,5	13,0	-9,8	9,9	0,4	-0,3
7	-6,5	6,4	0,3	-0,3	0,0	-0,0
8	10,0	-9,3	10,6	-10,6	1,1	-1,2

Table 4. Weight matrix between the first layer and the output layer.

Observed \ Predicted	1	2	3	4	5	6	7	8
1	26	0	2	0	0	0	0	9
2	0	27	3	0	0	0	0	0
3	0	0	20	3	0	0	0	6
4	0	0	0	21	0	0	0	0
5	3	0	0	5	29	0	0	0
6	0	0	0	0	0	24	2	0
7	0	0	0	0	0	4	26	4
8	0	1	3	0	0	0	1	8

Tabela 5. Matriz de confusão.

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