WAVELET ANALYSIS AND ARTIFICIAL NEURAL NETWORKS APPLIED TO CONDITION MONITORING IN HIGH SPEED MILLING

Irie Daniela Yamaguti Ebner
Technological Institute of Aeronautics
iriedaniela@yahoo.com

Jesus Franklin Andrade Romero
Technological Institute of Aeronautics
jesus@ita.br

Ademilson Zanandrea
Technological Institute of Aeronautics
ademil@ita.br

Osamu Saotome
Technological Institute of Aeronautics
osaotome@ita.br

Jefferson de Oliveira Gomes
Technological Institute of Aeronautics
gomes@ita.br

Abstract. *Despite its highly nonlinear behavior, the high-speed milling is one of the most common processes in modern manufacturing. As other complex processes, a suitable condition monitoring system is needed to guarantee the minimization of chatter problems. From a pattern classification perspective, the monitoring systems can be decomposed into three general tasks: data acquisition, feature extraction, and condition classification.*
The goal of this work is verify the relation between characteristics of stability and some cutting parameters regarding transient and steady state conditions. In this sense, techniques of digital signal processing and artificial intelligence are used. The wavelet transform approach combined with a neural network is used for feature extraction and classification. The analysis assumes a limited number of operation states, i.e. variations of the cutting speed, different tool geometries and tool engagement.

Keywords: *high speed milling, chatter, digital signal processing, and pattern recognition*

1. Introduction

High-speed cutting (HSC) exploits intensively the dynamic behavior of the machine-tool-workpiece system. The results of this type of process depend on the amplitudes of the relative vibrations between workpiece and tool, which arise during the operation. Eventually, these amplitudes can achieve unacceptable levels leading to a deteriorated surface finish and a reduction of the tool life. To avoid this situation, some cutting parameters are selected in order to keep the process in stable conditions (free of chatter). It must be noticed that inappropriate parameters may lead to the underutilizing of the machine functionalities, eventually decreasing the milling process speed.

Once several parameters must be adjusted in the milling process, the goal of this work is analyze some operation characteristics related to stable and unstable conditions. Notice that the analysis described in this work is considered initial in the sense of a development process that can provide a suitable parameter selection for stable end milling operations.

In this work, digital signal processing (DSP) techniques and pattern recognition concepts are used to analyze acoustic signals correlated to vibration signals that determine the surface finish. According to Smith and Tlusty (1976) microphone sensors supply suitable signals for the detection and vibration control in milling machines. The fast Fourier transform (FFT) is used to examine the steady state portion of the signal while the Wavelet transform (WT) is used for the transient portion. The difference between FFT and WT is the resolution of the analysis in low and high frequencies. Unlike FFT, in high frequencies the WT presents reliable results (Galli and Heydt, 1996).

The Fourier-based analysis of the acoustic signals was explored in Weingaertner et al. (2003) and Polly (2005), it must be stressed that the aim of this work is verify and extend some results considering the advantages of the WT in the transient portion of the signal. Also, we present an example of how a neural network could be used to classify the acoustic signals related to stability and instability conditions by means of a wavelet decomposition procedure as feature extractor of the complete signal (transient and stationary states).

The frequency signal based techniques used in this work are described in section 2. The section 3 presents the pattern recognition basic concepts and a neural network as a classification system. Analysis and results are presented in section 4. The concluding remarks are presented in section 5.

2. Time-Frequency Analysis of Acoustic and Vibration Signals

Since the use of High Speed Machinery technology has become more relevant in industrial systems, a rapidly identifier of stability behavior is required in order to improve productivity. Measurements that provide this information may be performed prior to (off line) or during (on line) machining. Several analytical methods were developed to determine the stability properties of the milling process, Minis and Yanushevsky (1993). Numerical simulation may also serve to provide a satisfactory result for this purpose, Balachandran (2001). In spite of all these research efforts, the identification of the critical chatter frequencies at the loss of stability is not a trivial task either experimentally or theoretically. The power spectra of the signals show several peaks of complicated structure. Some of them refer to the tooth pass excitation effect, others refer to the regenerative effect and the natural frequency (f_n) of the tool also appears.

In the following subsections, three signal processing techniques are described toward the rapid detect and classification of stable and unstable behavior of the milling process. The well-known Fourier transform approach is presented in section 2.1 with a briefly a description of how this technique is used as a design tool for milling operation monitoring systems. In section 2.2 quite promissory signal analysis techniques is described, more precisely, the Wavelet transform is introduced.

2.1. Fourier-Based Analysis

If a signal contains frequency components emerging and vanishing in certain time intervals, then a time as well as frequency localization is required. The traditional method proposed for such an analysis is the Short Time Fourier Transform (STFT). The STFT enables the time localization of a certain sinusoidal frequency but with an inherent limitation of the Heisenberg's uncertainty principle, which states that resolution in time and frequency cannot be arbitrarily small, because their product is lower bounded by $\Delta t\,\Delta f \geq (1/4\pi)$.

The Fourier analysis uses the propriety of how a signal can be decomposed into sine and cosine waves. The goal of decomposition is to end up with something easier to deal with than the original signal. The component sine and cosine waves are simpler than the original signal because they have a property that the original signal does not have: sinusoidal fidelity, i. e., a sinusoidal input to a system is guaranteed to produce a sinusoidal output. Only the amplitude and phase of the signal can change; the frequency and wave shape must remain the same. Sinusoids are the only waveform that has this useful property.

Minis and Yanushevsky (1993) examined stability of milling via Fourier analysis and basic properties of the parametric transfer functions of linear periodic systems. An infinite-order characteristic equation with constant coefficients was obtained and truncated to approximately determine system stability. Altintas and Budak (1995) introduced an alternate method to solve the stability problem in milling. They first derived the Fourier series expansion of the time-varying force coefficients and then used the first or first few expansion coefficients in the characteristic equation to compute the stability limit. For the high-speed cases they studied, this method achieves good results with only the first (average) Fourier term; nevertheless, this is an approximate solution.

2.2. Wavelet Analysis

Wavelet transforms do not consider a single set of basis functions (family of functions) like the Fourier transform, which utilizes just the sine and cosine functions. Using an infinite set of possible basis functions wavelet analysis provides immediate access to information that can be hidden by other time-frequency methods that don't provide any resolution in real space (for time series it means the time resolution). On the non-stationary signal analysis, the Wavelets locality properties lead us to their advantages over the Fourier Transform.

The wavelets functions compose an orthonormal system that can separate the local characteristics of a signal in different scales. Also, by means of translations, they cover all studied signal. Temporal analysis is performed with a contracted, high-frequency version of the mother wavelet, while frequency analysis is performed with a dilated, low-frequency version of the same wavelet.

In wavelet analysis, a signal can be decomposed in many levels of *approximations* and *details*. Approximations are the high-scale, low-frequency components of the signal, and the details are the low-scale, high-frequency components. A suitable level of decomposition is selected according to the signal and the task to be performed.

The original signal may be considered as the approximation at level 0, denoted by A0. The first step is to build the approximation A1 at level 1 and the detail D1 at level 1, Misity et al. (1996). The words approximation and detail are justified by the fact that A1 is an approximation of A0 taking into account the low frequencies of A0, whereas the detail D1 corresponds to the high frequency correction. Therefore, at each level j, the j-level approximation Aj (or approximation at level j) and a deviation signal called the j-level detail Dj (or detail at level j) are built, as shown in figure 1.

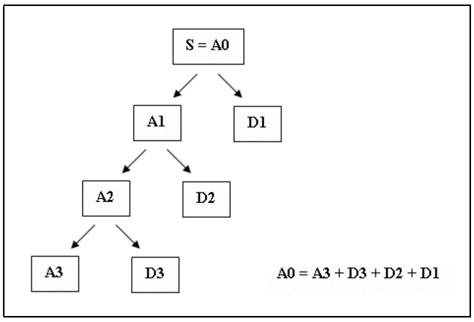


Figure 1. Three-level wavelet decomposition

Because the original signal or function can be represented in terms of a wavelet expansion (using coefficients in a linear combination of the wavelet functions), data operations can be performed using just the corresponding wavelet coefficients. The sparse coding shown in figure 1, makes wavelets an excellent tool in the field of data compression.

3. Pattern Recognition

Four steps basically compose a pattern recognition system: data acquisition, pre-processing, feature extraction and classification. An important task, when designing a pattern recognition system, is to identify which attributes are most relevant for decision making. In the feature extraction process, the features that hold the most relevant data information are identified and extracted. Hence, a feature measurement vector is constructed and the data pattern is determined. Once the patterns are presented to the system, it must be able to identify the pattern class. Bayesian classifier, Euclidean distance, neural networks and fuzzy systems are largely used as classifier system (Bishop, 1995).

In this work, a neural network is used to classify milling process acoustic vibration signals. Neural network is a form of multiprocessor computer system, with simple processing elements, a high degree of interconnection, simple scalar messages and adaptive interaction between elements. A neural network is a device with many inputs and N outputs, where N is the number of classes to be identified. The network has two modes of operation: the training mode and the testing mode. In the training mode, input patterns are presented to the neural network in order to create its generalization ability. In the testing mode, other input patterns are presented to verify the network's performance in pattern classification.

Neural networks presents several advantages (Bishop, 1995): capability of creating its own organization or representation of the information received during learning time; its computations may be carried out in parallel, and special hardware devices are being designed and manufactured with the advantage of this capability; they are universal approximators in the sense that they can theoretically approximate any continuous input-output mapping to any desired degree of accuracy; they have the ability to capture the underlying nonlinearity for the generation of incoming data.

In particular, neural networks are nonlinear. For many years linear modeling has been the commonly used technique in most modeling domains since linear models have well-known optimization strategies. Where the linear approximation is not valid (a frequently case) the models suffer accordingly. Neural networks also consider the curse of dimensionality problem that damage the attempts to model nonlinear functions with large numbers of variables. Regarding the inherently nonlinear characteristics of the milling process, the neural network becomes a suitable classification system to be used relating vibration acoustic signals with the milling stability and instability conditions.

4. DSP-based Stability Analysis

Since Tlusty (1965) and Tobias (1965) presented the first theoretical treatment in 1950s, chatter vibrations have been studied extensively and significant research has been reported on the dynamics high speed milling operations. Chatter vibrations continue to constrain high material removal rates and surface quality in end and face milling operations. This type of vibrations can be avoided by increasing the stiffness of machine tool-part structures, reducing the spindle speed to increase process damping, or selecting a spindle speed from stability charts. In particular, for HSC operation is not possible to increase the machine tool stiffness once the part geometry may not allow design modifications for higher stiffness. On the other hand, reducing spindle speed lowers the material removal rate, i.e. productivity. A practical solution would be to select a spindle speed and other cutting parameters from a stability analysis regarding the machine and material characteristics. In this sense, several methods were proposed regarding the chatter attenuation by tuning the process parameters using physical modeling and simulation analysis (Altintas and

Budak, 1995). This work presents an alternative path to identify stability conditions by means of time-frequency digital signal processing concepts and vibration sampled acoustic signals.

In the analysis of a high-speed end milling system, presented in Polly (2005), are identified suitable stability conditions when the harmonics of the tooth passing frequency (f_d) are distant from the system natural frequency. The stability evaluation, also used in this work, was based on the sound pressure analysis and a workpiece texture test was made in order to verify the milling quality. figure 2 presents the setup configuration used to sample the acoustic signal in all the tests.

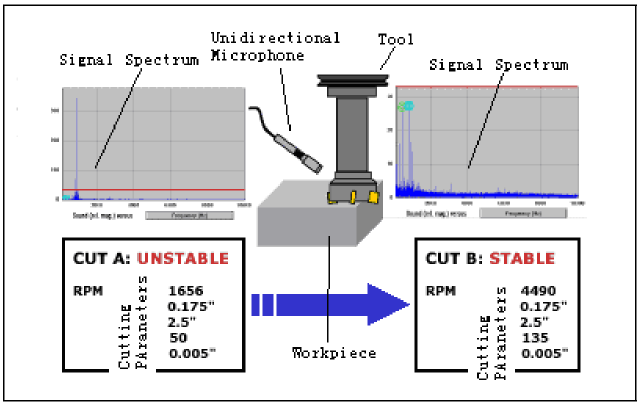
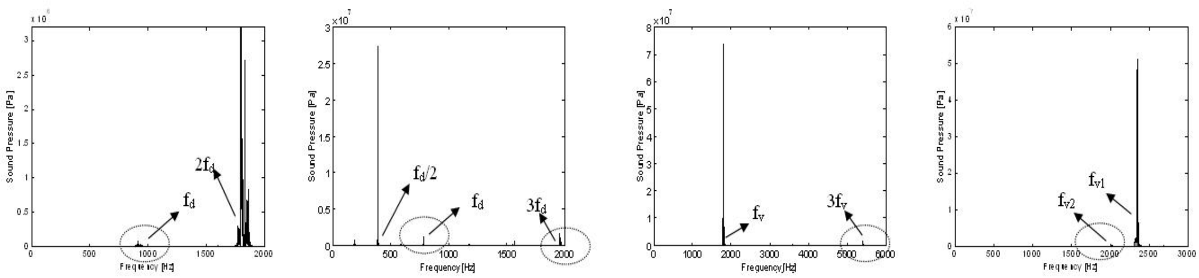


Figure 2. Experimental setup for the acoustic signal detection system

A microphone power supply (preamplifier type 2801 - Brüel and Kjaer, Copenhagen) and a unidirectional microphone (affixed to the turret machine) were used for acoustic vibration signal capture. The microphone bandwidth is 20 kHz; the amplifier gain was set to 20. All the sampled data were obtained of a 5 axes High Speed Hermle Machine (Model C6000) in the Center of Competence in Manufacture – CCM (Technological Institute of Aeronautics).

One of the main contributions of this work, by means of a transient and steady state analysis, is the verification and extension of some conclusive observations presented in Polly (2005) and Weingaertner et al. (2003). Instead of using the Fourier transform to analyze the characteristics frequencies of the steady state portion of the acoustic signal, in section 4.1 a short-time Fourier Transform is used to produce a time-frequency plot (spectrogram or Fourier power spectrum) representative of both transient and steady state portions of the sampled data. Additionally, the wavelet transform was introduced to overcome the resolutions problems usually identified when analyzing transient signals when using Fourier Transform. A suitable choice of a “basis function” to structure more reliable time-frequency representation turn the Wavelet transform a reliable option for power spectrum analysis. A total of 84 tests were accomplished in order to analyze the Wavelet decomposition technique in the end-milling process, a group of 4 tests are presented in section 4.2. In section 4.3 a Kohonen self-organizing map (neural network) is used to evidence the suitable properties of the decomposed signals to classify stability or instability conditions of the system and a group of 12 tests results are presented.

In order to describe the stability characteristics of the end-milling system under different operation conditions, the spectrum analysis (obtained by means of the Fourier Transform) of the sampled acoustic signal is presented in figure 3. Stability and instability conditions were verified using a threshold value of 0.8 μm in the surface roughness test (Ra). A four flute with 12 mm of diameter end mill tool was used in the following cutting tests and the dynamic characteristics of each test are presented in table 1.



a) Test 1 (f_d = 916 Hz) b) Test 2 (f_d = 783.33 Hz) c) Test 3 (f_d = 750 Hz) d) Test 4, (f_d = 666.66 Hz)

Figure 3. Frequency spectrum record for stable (a,b) and unstable (c,d) conditions

As figures 3a) and 3b) shows, the stable conditions tests are characterized by dominant frequency component values with a multiple or sub-multiple relation with the tooth passing frequency (f_d). As reported in Smith and Tlusty

(1990) and verified in Weingaertner et al. (2003), the stability operation condition is related to the fact that the tooth passing frequency values are close to the most flexible mode natural frequency. In the other hand, figures 3c) and 3d) presents unstable results where the dominant component frequencies, vibration frequencies (f_v), are not related to the system natural frequency.

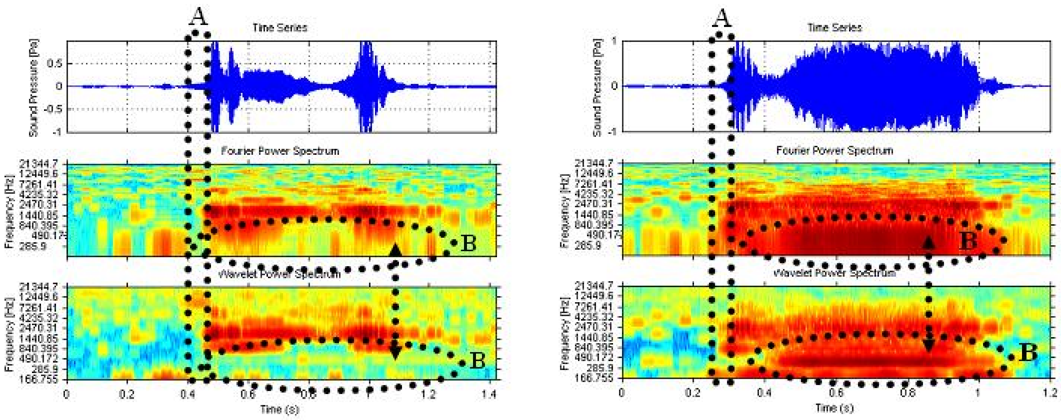
Table 1. Dynamic characteristics of the experimental implementation (figures 4-5)

Test	Condition	f_d (Hz)	f_v(Hz)	S(rpm)	a_p(mm)	f_z(mm/tooth)	L(mm)	Ra(μm)
1	Stable	916	-	13750	0.5	0.1	56.5	0.46
2	Stable	783.33	-	11750	1	0.1	43	0.75
3	Unstable	750	1800	11250	0.5	0.1	56.5	1.2
4	Unstable	666.66	2350	10000	1	0.1	43	1.0

f_d: tooth passing frequency, f_v: vibration frequency, S: spindle angular speed, a_p: axial depth, f_z: feed rate, Ra: Surface Roughness [μm] (obtained by a portable Surftest SJ-201P - MITUYO). End milling operations were performed on aluminum workpiece.

4.1. Acoustic signal spectrum analysis

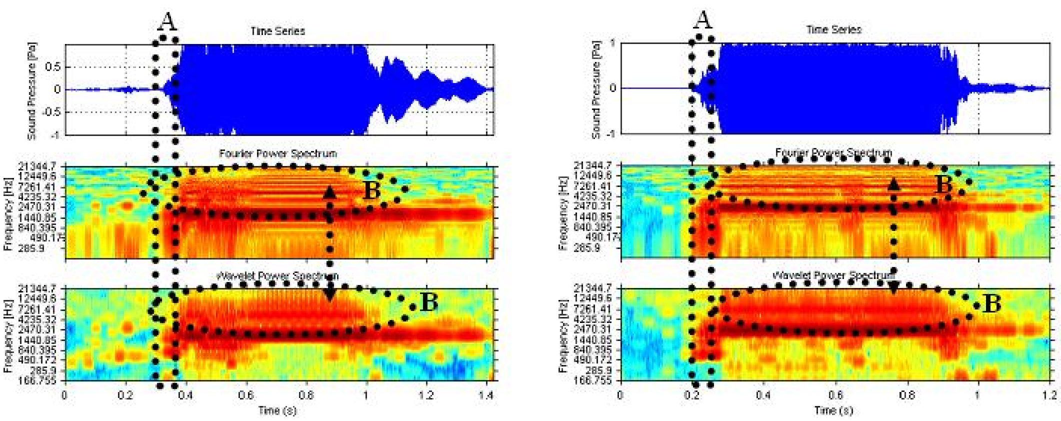
The discrete Fourier transform and the Wavelet transform are used in this section to extract local-frequency information for the signals related to stable (figure 4) and unstable (figure 5) end milling conditions.



a) Test 1 (f_d = 916 Hz)　　b) Test 2 (f_d = 783.33 Hz)

Figure 4. Fourier and Wavelet power spectrum of stable conditions signals

The feature extraction process begins with the separation of the vibration signal into smaller size different signals. Four different parts of the original signal are distinguished: steady state part, rising transient part, falling transient part and the idle part. The idle part is neglected because it doesn't contain information. Considering real time analysis systems the signal falling rising part is also out of interest. Considering that region A, in figures 4a) and 4b), involve the rising transient behavior of the vibration signals, it can be seen that the largest content of frequencies (denoted by the most intense red color region in the power spectrum plots) is stable in the spectrum analysis sense. More precisely, the most significant frequencies presented in steady state region are maintained in the transient region A.



a) Test 3 (f_d = 750 Hz)　　b) Test 4, (f_d = 666.66 Hz)

Figure 5. Fourier and Wavelet power spectrum of unstable conditions signals

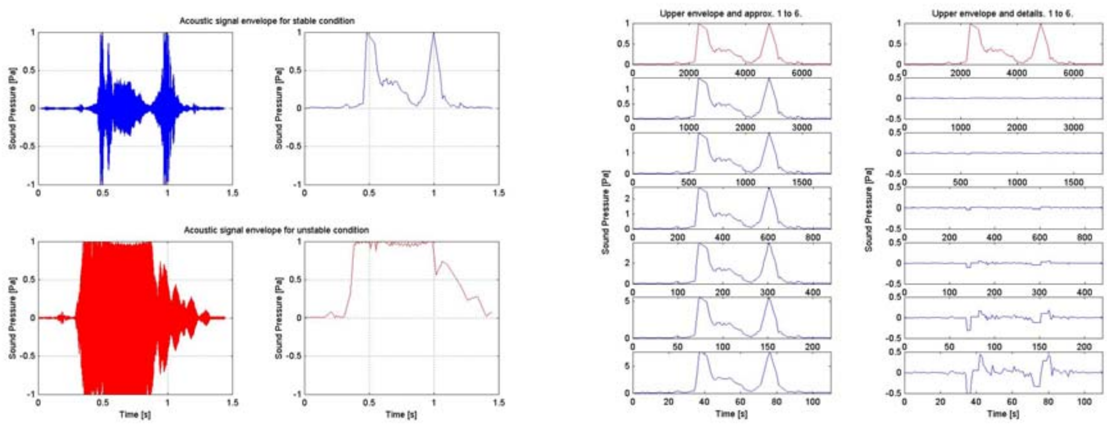
Due to its nature, the Fourier spectrum analysis can be applied only onto the steady-state part of a signal because it cannot represent small-extent transient vibrations, Haykin and Thomson (1998). Considering, however, that some other mechanical characteristics create abrupt variations localized in time, which are more intensely observed in the transient interval, motivate the use of wavelet instead of Fourier analysis. In order to expose the advantages of the WT, it is useful to compare it with the STFT, which has been extensively used for pre-processing data with localized features. The FT is a good method for analyzing stationary data, with the small-scale features (i.e., high frequency) representing the detail or noise presented in the signal, and the large-scale features (low frequency) representing the basic shapes. However, it has the disadvantage that the frequency information is global, because its basis functions are infinite duration sine and cosine functions. This is not satisfactory when searching for localized features. This problem is partially avoided by using the STFT or windowed FT, where the signal is analyzed locally. However, the STFT uses a fixed size window in its original (time) domain, the same for large and small-scale components of the signal. What is really needed is a long window to analyze large-scale components and a narrow one to detect the small-scale features. This problem is overcome by WT due to its dilatation and translation characteristics. This is exactly what figures 4 and 5 presents through the marked regions B. As it can be seen, a “Morlet” Wavelet signal with 8 scales and a resolution of 0.25 structures a Wavelet spectrum plot with better resolution characteristics in high and low frequencies.

4.2. Acoustic signal wavelet decomposition

WT is a domain transform technique for hierarchically decomposing sequences. It allows a sequence to be described in terms of an approximation of the original sequence plus a set of details that range from coarse to fine. One property of wavelets is that the broad trend of the input sequence is preserved in the approximation part, whereas localized changes are kept in the detail parts. No information is gained or lost during the decomposition process. The original signal can be fully reconstructed from the approximation part and the detail parts (Zhang et al. 2004).

The main objective of the analysis is to extract information from the original signal through this decomposition into a series of approximations and details distributed over different frequency bands. The computed coefficients in these sequences form the wavelet decomposition of the measured signal *s*. The coefficients in the sequences D (details) can be interpreted as the details of the signal *s* at coarser resolutions as the decomposition level is increased.

In this work, wavelet decomposition is used as a feature extractor technique in order to classify acoustic vibration signals. Assuming that the signal scale energy is concentrated in a group of few coefficients, it can be used to represent the whole signal with low error characteristics and reduce the original data dimension. At each level N, after low-pass signal filtering, a down-sampling is made reducing data dimension at ratio 2^N. In order to extract the main characteristics of the vibration signals, the upper envelope is computed and decomposed in 6 levels and construct the feature patterns. In figure 6a), stable and unstable signals with their upper envelopes are presented.



a) Envelope of stable and unstable vibration signals b) Six-level decomposition of a stable envelope signal

Figure 6. Wavelet decomposition

Considering two classes to be identified and regarding the shape differences between the signals, the selection of a 6-level approximation is used in order to hold more low-frequency characteristics. In case of signals of different classes that present more similarity, a lower level decomposition, or the details coefficients utilization could produce better results. A stable signal envelope and its decompositions can be seen in figure 6b). Note that the approximations are the high-scale, low-frequency components of the envelope signal, and the details are the low-scale, high-frequency components. The energy values or the coefficients themselves, for all or a selected number of levels, are chosen as the essential signal characteristics. Each acoustic vibration signal is decomposed in 6 levels of approximation and details and its coefficients built a feature vector as a sample pattern to be presented to a neural network classification system.

4.3. Acoustic signal classification

Neural networks, with their remarkable ability to detect meaning information from imprecise data, can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques. Due to its nonlinear characteristic, neural network has been extensively used in several application areas as mentioned in section 3.

Due to the acoustic vibration signal shapes, Kohonen's self-organizing map was selected to signal classification once the signal shapes of stable and unstable milling has presented a visible difference. Since a harmony with statistical regularities of input data is achieved, the network presents a developed ability to form internal representations in order to codify input data characteristics, creating new classes or groups automatically (Bishop 1995).

As mentioned in the section 4.2, input pattern is constructed through the wavelet decomposition. Since the envelope signal is composed by a high number of samples (7040 points), after a 6-level decomposition procedure, the approximation signal is reduced to 110 points. Therefore, the network's input layer is composed by 110 neural processors. The output layer presents 6 neural processors although there are only 2 classes to be identified. In this sense, the first three processors correspond to stable milling while the last three processors identify instable milling. If the activated output processor is one of the first three processors, then the signal represents a stable milling process. Otherwise, the signal corresponds to an unstable milling process. The neural network's configuration can be seen in figure 7.

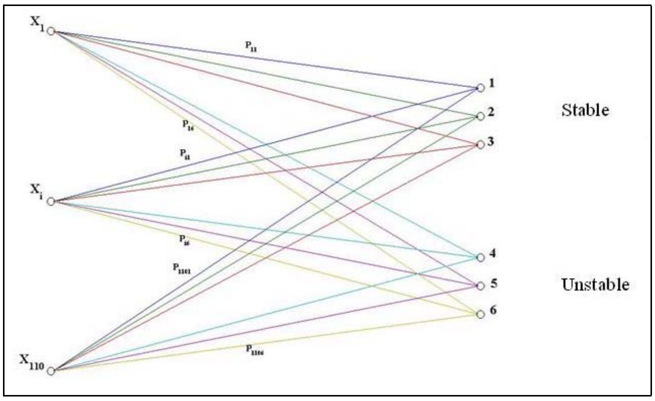


Figure 7. Kohonen's self-organizing map configuration

A set of twelve samples was available to the network containing 4 stable milling samples and 8 unstable milling samples. Considering the axial depth values used in the end-milling tests, some difficulties in determining stable milling parameters were found and a limited database was constructed. In order to speed up the training time, the connection weights were initialized inside signal values range. After training process, tests were carried out evaluating the network's classification. The results are presented in table 2.

Table 2. Kohonen's self-organizing map results

Acoustic vibration signal	Activated output neural processor	Neural network's response
Test 1 – unstable milling	4	unstable milling
Test 2 – unstable milling	4	unstable milling
Test 3 – unstable milling	4	unstable milling
Test 4 – unstable milling	4	unstable milling
Test 5 – unstable milling	4	unstable milling
Test 6 – unstable milling	4	unstable milling
Test 7 – unstable milling	4	unstable milling
Test 8 – unstable milling	4	unstable milling
Test 9 – stable milling	6	unstable milling
Test 10 – stable milling	3	stable milling
Test 11 – stable milling	2	stable milling
Test 12 – stable milling	2	stable milling

From the above classification results, the Kohonen's self-organizing map developed in this work has presented good generalization capability with just one signal wrongly classified. Since the acoustic vibration signals of stable and unstable milling process present visible shape differences, the use of a simple neural network could obtain good results.

Nevertheless, in case of similar signals of different classes, more attention and a better study in neural network selection and construction must be done.

5. Conclusion

The characteristics of high-speed end-milling process were investigated using two different DSP techniques (Fourier and Wavelet transforms). Time-frequency characteristics of the vibrations signal, considering transient and stationary states, were analyzed. The main contributions of this work can be summarized as follows: a) A time-frequency analysis procedure is proposed aiming the study of the rising transient frequency components in vibration signals. b) It was verified that Wavelet transform technique is a powerful tool in vibration signals analysis due to its better resolution in high and low frequencies and feature extraction capabilities. c) Since the signals generated by the milling process are inherently nonlinear and nonstationary, and considering that neural networks can acquire relevant nonlinear characteristics of this type of systems, a Kohonen self-organizing map is used to evidence the suitable properties of the decomposed signals in order to classify stability or instability conditions.

Finally, some suggestions for future works related to this article are listed: a) Compute the WT considering only the transient state signal of vibration time series objectifying an instability detection system that could avoid the tool or material damage. b) Since the acoustic vibration signals of stable and unstable milling process present visible shape differences, with a simple neural network good results were obtained. In order to identify new sub-classes originated from instability class, a new neural network selection and construction must be studied.

6. Acknowledgements

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8. Responsibility notice