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### Fault Diagnosis using Audio and Vibration Signals in a Circulating Pump

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**Abstract.** This paper presents the use of audio and vibration signals in fault diagnosis of a circulating pump. The novelty of this paper is the use of audio signals acquired by microphones. The objective of this paper is to determine if audio signals are capable to distinguish between normal and different abnormal conditions in a circulating pump. In order to compare results, vibration signals are also acquired and analysed. Wavelet package is used to obtain the energies in different frequency bands from the audio and vibration signals. Neural networks are used to evaluate the discrimination ability of the extracted features between normal and different faulty conditions with a success rate of 83.33%, 98% and 91.33% for each microphone respectively. These success rates are similar and even higher that those obtained from accelerometers (68%, 90.67% and 71.33% for each accelerometer respectively). Success rates also show that the position of microphones and accelerometers affects on the final results.

#### 1. Introduction

Condition monitoring techniques and its role in fault diagnosis have attracted researchers in last decades due to their great influence on the operational continuity of many industrial processes. The correct fault diagnostic and early fault detection leads to faster and more effective maintenance, avoiding serious damage in machines and increasing the reliability, security and fault tolerance in industrial scenarios. Pumps are important components in a wide range of technical processes, such as power stations, chemical industry and air conditioning, cooling and heating systems. The degradation of impellers, bearing and other parts of the pump can reduce its performance or even can produce the fail of the pump system. The overall reliability and safety of many systems depends on the health of pumps. Therefore, the monitoring and fault diagnosis of pumps plays a key role in maintenance procedures.

The main faults in pumps are associated with impeller damages [1][2], rotor faults, seals faults, cavitation [2] and bearing faults [2][4]. Pump monitoring is mainly addressed using vibration analysis in frequency and time domain. Zhao et. al [1] analyzed the pump frequency and harmonics in a slurry

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pump with impeller damages and applied neighbourhood rough set models to select features. Statistical features such as standard deviation, skewness and kurtosis were extracted from vibration signal of a centrifugal pump to detect between normal and faulty condition (impeller fault, seal fault, bearing fault and cavitation) using a C4.5 decision tree algorithm [2][3]. Frequency analysis was also used to detect the remaining useful life of pump bearings using a neural network approach [4] and power spectral analysis was applied in detecting bearing and gear faults in hydraulic pump [5]. Five-plunger pumps were diagnosed using features extracted from frequency spectra and then processed using fuzzy membership function [6]. Acoustic emission technology for detecting cavitation in pumps was also investigated in [7] using rms levels and frequency analysis. Frequency and time analysis have limitations in fault diagnosis because these methods cannot track non-stationary and non-linear components of signals.

Wavelet analysis is a prominent technique widely used in fault diagnosis applications [8]-[10]. Wavelet transform (WT) is an extended time-frequency domain analysis method to identify local characteristics signals decomposing time domain signals according to their frequencies [11] by means of an adjustable window size and different approximation scales. This flexibility makes it very suitable for the analysis of non-stationary signals and allows a finer analysis of the signal. Wavelet Package Transform (WPT) is a variant of the discrete wavelet transform. WPT decomposes the signal in both low frequency and high frequency components [10]. WPT can conduct comprehensive time-frequency decomposition of signals, so it can reflect time-frequency characteristics more accurately. Wavelet analysis has been applied in vibration and pressure fault diagnosis of centrifugal pumps and progressing cavity pumps [12]-[14].

In this paper, the use of audio and vibration signals in monitoring the impellers of a circulating pump is proposed. The objective is to determine if audio signals are capable to distinguish between normal and different abnormal conditions in a circulating pump and to use the vibration signal in order to compare results. The novelty of the paper is the use of audio signal in pump monitoring. To author knowledge, no previous work has used audio signals to monitor impeller pumps. Audio-based monitoring is less intrusive than vibration-based monitoring because microphones are not mounted on the machine, whereas accelerometers are. Vibration and audio signals are simultaneously acquired from three microphones and three accelerometers placed in different positions around and on the pump. A database is collected with different impeller states: normal impeller, impellers without a blade and impellers without two blades. Energy features are extracted from the wavelet package transform of the raw audio and vibration signals. Finally, the system is evaluated with a neural network classifier and different success rates are obtained for the different sensors. The results show that information from sound signals can distinguish between normal and different faulty conditions.

The structure of this paper is as follows. In section 2, the basis of wavelet package transform is explained briefly. The experiment is presented in section 3 including the database acquisition, feature extraction, neural network classifier and data fusion. In section 4, the results are shown and finally, section 5 is devoted to the conclusions.

#### 2. Wavelet Package Transform and energy features

Wavelet transform decomposes a signal onto a set of basis functions called wavelets. These are obtained from a single prototype wavelet, called mother wavelet, by dilatations and contractions, as well as by shifts. Wavelet package transform is a generalization of the wavelet transform and the wavelet packet function is also a time-frequency function. WPT can simultaneously break the signal up into detail (low frequency components) and approximations signals (high frequency components) in different levels of decomposition or scales. WPT can be defined as follows [10]:

$$W_{l,k}^{n}(t) = \sqrt{2W^{n}(2^{l}t - k)}$$
(1)

where j and k are the scale and translation index. The index n is an operation modulation parameter. The first two wavelet packet functions are the scaling and mother wavelet functions (equation (2) and equation (3)).

$$W_{0,0}^0(t) = \phi(t)$$
 (2)

$$W_{0,0}^{1}(t) = \psi(t)$$
(3)

When n = 2, 3, ... the function can be defined by the following recursive relationships: The first two wavelet packet functions are the scaling and mother wavelet functions (equation (2) and equation (3)). in different levels of decomposition or scales. WPT can be defined as follows [10]:

$$W_{0,0}^{2n}(t) = \sqrt{2} \sum_{k} h(k) W_{1,k}^{n}(2t-k)$$
(4)

$$W_{0,0}^{2n+1}(t) = \sqrt{2} \sum_{k} g(k) W_{1,k}^{n}(2t-k)$$
(5)

where h(k) and g(k) are the quadrature mirror filter associated with the scaling and mother wavelet function. The wavelet package coefficients  $w_{l,k}^n$  are computed by the inner product  $\langle f(t), W_{l,k}^n \rangle$ :

$$w_{l,k}^{n} = \left\langle f(t), W_{l,k}^{n} \right\rangle = \int f(t) W_{l,k}^{n}(t) dt$$
(6)

Therefore, by applying the WPT to the original signal, wavelet package coefficients are obtained at different frequency bands depending on the level of decomposition. In this paper, the vibration and sound signals are broken up to 5 level (*l*=5) of decomposition, obtaining 32 frequency bands (or 32 nodes) in this level of decomposition. Signals can be reconstructed from the wavelet coefficients associated to each node. The reconstructed signal for each node is a new time series. If x(n) denotes the original signal (the audio or the vibration signal), then  $x_{l,k}(n)$  is the reconstructed signals for *l*th level of decomposition ( $l = 1 \dots, L$ ; *L* is the number of decomposition levels) and *k*th denotes the frequency-band signal ( $k = 1, \dots, K$ , *K* is the number of decomposed frequency-band signals and it equals 2'). For example, for *l*=5, there are  $2^5=32$  frequency-band signals on level 5. In figure 1, the decomposition process of the WPT with L = 5 is depicted and the frequency ranges associated with the reconstructed signals in each node are shown. This kind of representation is called wavelet package tree. In figure 1,  $f_N$  denotes the frequency band of the signal x(n). In this paper, the sample frequency is fs = 44100 Hz and  $f_N = 22050$  Hz. Therefore, x(n) has a frequency interval (0,22050]Hz,  $x_{5,0}(n)$  is the reconstructed signal in level 5 with a frequency range of (0, 689.06]Hz and  $x_{5,31}(n)$  is the reconstructed signal in level 5 with a frequency range of (21360.94, 22050]Hz.



Figure 1. Wavelet Package tree: decomposition of the original signal with wavelet package transform. fn is the signal bandwidth and equals 22050Hz.

In this paper, relative energy features are computed from the reconstructed signals in level 5 of decomposition (l = 5). *E* denotes the energy of the original signal x(n):

$$E = \sqrt{\frac{\sum_{i=1}^{N} (x(i) - x_m)^2}{N - 1}}$$
(7)

where  $x_m$  is the mean value of x(n) and N is the number of samples of x(n). Then, the relative energy of the reconstructed signals in level 5 is computed as: decomposition (l = 5). E denotes the energy of the original signal x(n):

$$e_{k} = \frac{\sqrt{\sum_{i=1}^{N} (x_{5,k}(i) - x_{m_{5,k}})^{2}}}{\frac{M-1}{E}}$$
(8)

where  $x_{5,k}(n)$  (k = 0,...,31) are each of the reconstructed signals of level 5, *M* is the number of samples of  $x_{5,k}(n)$  and  $x_{m_{5,k}}$  is the mean value of each  $x_{5,k}(n)$ . The features extracted from audio and vibration signals are *E* and  $e_k$ . These are the diagnostic feature vectors.

#### 3. Experimentation

In this paper, we present a study of the vibration and audio signals in detecting failures in a circulating pump. The main objective is to show the capability of audio signal to detect failures in circulating pumps. This section focuses on the different steps of the experimental procedure: database acquisition, where three audio signals and three vibration signals are acquired simultaneously, feature extraction of each of the signals using the wavelet package transform and finally, the evaluation of the different signals with a neural network classifier (see figure 2).



Figure 2. Steps of the experiment.

#### 3.1. Database acquisition

The setup of the experiment is shown in figure 3, where the circulating pump and the sensors are shown. The circulating pump is the ALP 800 M with 2925 rpm and 0.5 HP. The rotor frequency of the pump is 48 Hz approximately. The impeller has 7 blades, so the vane passing frequency is 350 Hz approximately. The tank is filled with 50 liters of water and a closed loop is formed with pipes. Three accelerometers are placed in three orthogonal directions over the pump casing: two accelerometers CESVA AC001 with sensitivity  $100 \pm 5 \%$  mV/g (ACELER1 and ACELER2) and one accelerometer CESVA AC006 with sensitivity  $1000 \pm 10 \%$  mV/g (ACELER3). Three prepolarized condenser microphones CESVA MX025 are placed at 5 cm approximately from the pump (MICRO1, MICRO2 and MICRO3). ACELER1, ACELER2, ACELER3, MICRO1, MICRO2 and MICRO3 correspond to accelerometer 1, accelerometer 2, accelerometer 3, microphone 1, microphone 2 and microphone 3 respectively.

The sensors are connected to the inputs of a front-end FC-822 where the signals are amplified with 30dB of gain. The front-end is connected to three external cards to the computer, where the signals are stored and then processed. The recording software acquires the six signals simultaneously. The sample frequency of the acquisition system is 44100 Hz.

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Signals are obtained in normal condition and in two faulty conditions: one blade of the impeller is removed (1B fault), and two blades of the impeller are removed (2B fault). The impeller in normal and faulty conditions is shown in figure 4. Four signals of 1 minute are obtained for each condition and for each sensor in four different recording sessions. Therefore, we have 12 files for each sensor (4 files for each conditions) and 72 files in total (12 files for each sensor x 6 sensors).



Figure 3. Experimental setup. General view (a) and zoom of the sensors (b).



Figure 4. Impeller in normal condition (a), with one blade removed (b) and with two blades removed (c).

#### 3.2. Data processing: feature extraction

In the feature extraction step, each file is divided into frames of 100ms corresponding to 5 revolutions of the rotor of the pump approximately and to 35 revolutions of a blade. Wavelet package transform is computed for each frame using two different mother wavelets: daubechies 6 (db6) and symlet 2 (sym2). The level of decomposition is 5 in both cases, so 32 terminal nodes are obtained. The 5 levels of decomposition of the wavelet package provide great resolution for the analysis. Then, signals are reconstructed from the 32 terminal nodes of the wavelet package tree, obtaining 32 reconstructed signals. The energies of the original signal (i.e. a frame) and of the reconstructed signals are computed. Finally, the energy of each reconstructed signal is divided by the energy of the original signal. So, 33 energy features are computed for each frame and a matrix of 600 frames x 33 features is obtained for each file. These features feed a neural network to evaluate the discrimination ability of the features between normal and faulty conditions.

The energy features extracted from the reconstructed signals of the 5-layer WPT terminal nodes for one frame are shown in figures 5, 6, 7 and 8. Each bar represents the relative energy of each terminal node (from 1 to 32 terminal nodes). Figure 5 and figure 6 depict each pump condition (N, 1B, 2B) for each accelerometer and for each microphone using the 'db6' mother wavelet. Figure 7 and figure 8 show the same information using the 'sym2' wavelet mother.

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The differences in energy distribution of the frequency subbands between normal and faulty conditions are evident in all figures. In general, for all sensors, the energy is concentrated in terminal nodes from 1 to 8, corresponding to frequency range from 0Hz to 5512Hz approximately. This shows that the energy is concentrated in low frequencies until the 15<sup>th</sup> harmonics of the fundamental frequency of the pump (350Hz). Figures also show that there are differences in energy between the same kinds of sensors. For example, accelerometer 2 has more energy contribution in higher frequencies than accelerometer 1 and 3. This fact shows the importance of the sensor position.



Figure 5. Energy features extracted from the reconstructed nodes of the 5-layer

wavelet package transform for one frame using 'db6' as wavelet mother. Each pump condition (normal, 1-blade fault condition and 2-blades faulty condition) are shown for accelerometer 1 (a), accelerometer 2 (b) and accelerometer 3 (c).



**Figure 6.** Energy features extracted from the reconstructed nodes of the 5-layer wavelet package transform for one frame using 'db6' as wavelet mother. Each pump condition (normal, 1-blade fault condition and 2-blades faulty condition) are shown for microphone 1 (a), microphone 2 (b) and microphone 3 (c).



**Figure 7.** Energy features extracted from the reconstructed nodes of the 5-layer wavelet package transform for one frame using 'sym2' as wavelet mother. Each pump condition (normal, 1-blade fault condition and 2-blades faulty condition) are shown for accelerometer 1 (a), accelerometer 2 (b) and accelerometer 3 (c).



**Figure 8.** Energy features extracted from the reconstructed nodes of the 5-layer wavelet package transform for one frame using 'sym2' as wavelet mother. Each pump condition (normal, 1-blade fault condition and 2-blades faulty condition) are shown for microphone 1 (a), microphone 2 (b) and microphone 3 (c).

#### 3.3. Neural Network classifier

The discrimination ability of the features for each sensor is evaluated using a neural network classifier, i.e. there are 6 different neural network classifiers for each sensor. Features extracted using 'db6' mother wavelet and features extracted using 'sym2' mother wavelet are evaluated independently. For

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each classifier, multilayer feedforward neural networks with one hidden layer with 15 neurons are used. Supervised learning is carried out using resilient backpropagation train algorithm. The input layer is made up of either as many inputs as features. The output layer has three nodes, the number of classes to be classified: normal, 1B fault (one blade removed) and 2B fault (two blades removed). The activation functions on the hidden nodes are tansigmoids (hyperbolic tangents) and the activation function of the output node is linear. The connection weights and biases are initialized according to the Nguyen–Widrow initialization algorithm. The training process is stopped when a relative error of 0.015 is reached.

The database is split into a training subset and a testing subset with 3 files for training set and 1 file for testing set of each condition. The data in the training set are z-score normalized. The test set is normalized by subtracting the training set mean and dividing by the training set standard deviation for each feature. The experiments were repeated 50 times, each time using different training and test sets randomly chosen. Then, each file is classified according to the more voted classified frames in the evaluated file. Finally, the results of each repetition are averaged and the success rate is computed for each sensor and for each group of features (features from 'db6' mother wavelet and features from 'sym2' mother wavelet).

#### 3.4. Data fusion

Different sensors are evaluated together in order to study the impact in performance. For this reason, the evaluation of the neural network is also accomplished using the features extracted from the three accelerometers altogether as inputs for a neural network classifier. The same procedure was accomplished with the features extracted from the three microphones. Finally, the features extracted from individual sensors of each kind (accelerometers and microphones) that obtain the best individual success rates are evaluated together.

#### 4. Results

The results of individual sensor evaluation are shown in table 1 for 'db6' and 'sym2' wavelet mother (first raw and second raw of the table respectively). The results show that information from sound signals can effectively distinguish between normal and faulty conditions in impellers of a circulating pump. The success rates of microphones are even higher than those obtained from accelerometers. In the comparison of the results between the mother wavelets 'db6' and 'sym2', it can be observed that the results are quite similar, although 'sym2' has slightly better results than 'db6'. These results are consistent with the visual inspection of the features in section 3.

	ACELER1	ACELER2	ACELER3	MICRO1	MICRO2	MICRO3
'db6'	60%	85.33%	70%	88.66%	94%	95.33%

 Table 1. Global success rates for each sensor using 'db6' and 'sym2' as mother wavelets.

The success rates also show that the position of microphones and accelerometers affects on the final results. According to the individual results, the best success rates are obtained for accelerometer 2 for both 'db6' and 'sym2', for microphone 3 in the case of using 'db6' and for microphone 2 in the case of using 'sym2'.

The results of the feature combination for the three accelerometers and for the three microphones are shown in table 2. According to the results, the combination of accelerometers do not increase the success rate, however the combination of microphones results in a higher success rate. Table 2 also shows the combination of accelerometer 2 and microphone 2 and the combination of accelerometer 2 and microphone 3. The combination increases the success rates of the individual results in the case of combining accelerometer 2 and microphone 3 using 'sym2' as mother wavelet.

**Table 2.** Global success rates for the combination of accelerometers, microphones, accelerometer 2 and microphone 2, accelerometer 3 and microphone 2 using 'db6' and 'sym2' as mother wavelets.

	ACCELEROMETERS	MICROPHONES	ACELER2+	ACELER2+
			MICRO2	MICRO3
'db6'	81.33%	100%	86.67%	92.67%
'sym2'	86%	99.33%	96%	94.67%

#### 5. Conclusions

In this paper, audio and vibration signals were simultaneously acquired from a circulating pump in normal and faulty conditions of the impellers using three microphones and three accelerometers. Energy features were extracted from wavelet package transform of the audio and vibration signals and the discrimination ability of the features were evaluated using a neural network classifier. Two different mother wavelets were used in the experiments ('db6' and 'sym2'). Audio and vibration signals were evaluated independently and altogether. The objective of this paper is to show that audio-based pump monitoring can distinguish between different pump conditions.

The results of the evaluation of the audio and vibration signals showed that audio signals are an effective tool to distinguish between normal and impeller faults in a circulating pump. The success rates obtained using microphones (88.66%, 94% and 95.33% for each microphone using 'db6' mother wavelet and 83.33%, 98% and 91.33% for each microphone using 'sym2' mother wavelet) showed to be higher to those obtained using accelerometers (60%, 85.33% and 70% for each accelerometer using 'db6' mother wavelet). The main advantage of using microphones in fault diagnosis is its non-invasive nature, because they are not mounted directly on the machine.

According to the results of the experimentation, some conclusions can be obtained. Firstly, the success rates obtained using audio signals are better than the success rates obtained with vibration signals. Secondly, the position of the sensors affects the results. The accelerometer in the inlet part of the pump has better results and the other accelerometers and the microphones placed near the inlet of the pump has also better results than the microphone pointed to the outlet of the pump. Thirdly, the results obtained. Finally, the combination of features extracted from accelerometers does not increase the success rates of individual accelerometers. However, the combination of features extracted from microphones. Moreover, the combination of audio and vibration signals increases the success rate in the case of using 'sym2'.

The results of this paper encourage us to follow the research using audio signals. Future research is aimed to the study of other pump failures using audio signals. A deeper study is necessary in the fusion of audio and vibration signals at different stages in the process.

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