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GEAR FAULT DIAGNOSIS AND CLASSIFICATION USING DATA VIBRATION

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ABSTRACT

Gear is considered as a critical component in machinery elements, their failure caused an unexpected disturbance at industrial processes. Many researchers studied diagnose of gear faults by vibration data analysis. In this regard, we create and develop a vibration database from an industrial plant, then we apply many methods to extract features and we classify gear-faults based on different algorithms. We consider four gear fault classes: healthy gear, with pinion defect, with wheel defect and with both pinion and wheel defects. We perform diagnosis using temporal and spectral analysis, than we improve the fault classification results using appropriate feature extraction combined to nonlinear classifiers. The excellent classification scores in the experimental phase proofs the effectiveness of the proposed methods.

Keywords: machine vibration, gear condition monitoring, faults diagnosis, classification, feature extraction.

1. INTRODUCTION

Gears are rotating machine part needed for motion transmission in industrial applications such as conveyors, wind power generators, elevators and pumps. There failures caused unscheduled downtime leading high productivity losses and huge maintenance costs. Vibration analysis can be considered as a useful way to diagnose and classify typical faults [1], such as pinion and wheel faults, cracked shaft, misalignment, unbalance, rubbing, motor faults and bent shaft defects. To avoid the complexity due to gear dynamical model, we use, for faults diagnosis, data driven models based on historical data [8, 9]. The gear diagnosis can be done in the time or in the frequency domain [1, 16]. In the first one, Root Mean Square (RMS), skewness, kurtosis and crest factor are the most popular statistical time domain parameter for faults diagnosis. In the frequency domain, the enveloping technique has been proven to be an efficient method for gear defects detection. In recent years, the neural networks, genetic algorithms and the wavelet transform have emerged as excellent process for fault detection [3, 5, 17].

A gear fault diagnosis can be decomposed into three parts: data acquisition, feature extraction, and fault condition classification. The aim of this paper is to present a methodology by which different gear defects can be detected and classified. We present the conception and the exploitation of a gear vibration database taking in an industrial plant and we present also different methods used to extract and classify gear-faults. For improving the classification accuracy, we use K-Nearest Neighbors (KNN) and multi-class Support Vector Machine (SVM) classifiers as machine learning algorithms. Those methods are combined with feature extraction parameters: Temporal, spectral, alpha stable and wavelet. The experimental measures and treatment are applied to gear radial axis. The proposed methods are built and applied to perform to automate the fault diagnosis and classification procedure.

We present in Section 2, the adopted approach, the experimental phase is detailed in section 3, while section 4 exposed the obtained results and discussions. Finally, section 5 gives conclusions and remarks.

2. THE RESEARCH METHOD

2. 1 Feature extraction

To diagnose gear faults, we process in three phases (see Figure-1): Data acquisition, a learning phase by a feature extraction, and fault condition classification. In the first phase, we construct a gear vibration database using radial accelerometers, in the second one, we diagnose faults gear based Fast Fourier Transformation (FFT) and we extract reliable features based many methods and algorithms: Temporal, spectral (based acceleration spectrum (AS), Power Spectrum (PS), Density Power Spectrum (DPS)), wavelets and α-stable distribution.

These features are then used to learn several behavioral models corresponding to different initial states and operating conditions of gears (Healthy and fault states). The last phase, we detect the component's condition by exploiting the learned models, in this phase we use KNN and SVM classifier algorithms, for estimate gear state and we compute the identification scores, classification scores and the corresponding recognition accuracy. The learned models are exploited to identify the gear defect type (in our study we have considered four gear fault classes: Normal, pinion fault, wheel fault and pinion/wheel faults).

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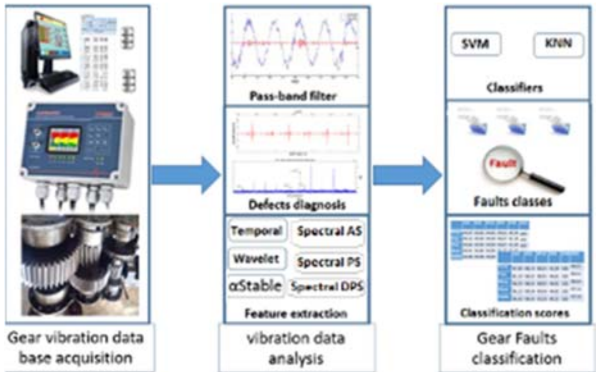

Figure-1. Gear fault classification approach.

We use for temporal, spectral and wavelet extractions [2, 6], five indicators (RMS, Peak Level, Crest Factor, Kurtosis and Entropy). In each case, we apply them to acceleration signal, acceleration spectrum; power spectrum, density power spectrum and the third level wavelet decomposition (see Table-1).

Table-1. Feature extraction parameters.

	Signals	**Parameters**
Temporal	**Acceleration**	RMS Peak Level Crest Factor Kurtosis Entropy
Spectral	Acceleration spectrum (AS)	
	Power Spectrum (PS)	
	Power Spectrum Density (PSD)	
Wavelet	The means of the eight parquets using the third level wavelets decomposition (dB02)	
α Stable	Acceleration	Alpha stable parameter's

We use also an extraction based alpha stable distribution [7, 12], which includes Gaussian, Cauchy and Levy distributions as special cases. This distribution was developed from the generalized central limit theorem. The general characteristic function for this probability density is characterized by a four-parameter family of continuous probability distributions form roughly corresponding to measures of asymmetry and concentration. We use the four parameters of alpha stable distribution as features in fault diagnosis of gear. The calculated features represent the degradation of gear.

2.2 Faults classification

We use as nonlinear classifiers, the multi-class Support Vector Machine (SVM) [4, 11] a computational learning method which employs structural risk to minimize an upper bound on the expected risk, it's considered as one of the most efficient classification algorithm.

We use also the K-Nearest Neighbors algorithm (KNN) [10, 15] a machine learning algorithm used in pattern recognition as a non-parametric method. Its input is the k closest training examples in the feature space and its output consists of a class membership.

2.3 Experimental section

The experiment was carried on many gears with the characteristics shown in the Figure-2. Those gears are entrained by a three phase's 18.5Kw and 1500 rpm motor, they have parallel shafts, a bubbling lubrication and 1/14 as reduction ratio. For measurement, we consider full load condition and we use as sensors the piezoelectric accelerometers mounted with magnetic bases fixation. The obtained radial vibration signals of four gears have a 25.6 KHz sampling rate and the acquisition duration for each Gear is 40Sec. The same experimental platform was performed for sleeve and ball bearing [13, 14].

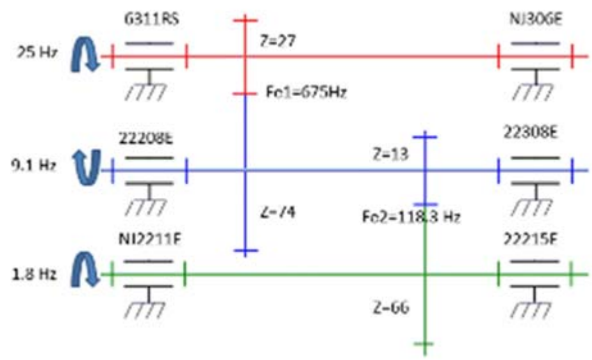

Figure-2. Gears characteristics.

The industrial ICP accelerometers are connected to the vibration card NI 9234 as input NI CompactRIO-9022 controller module. The NI-controller is connected to a computer for advanced treatment: Features extraction and fault classification. LABVIEW software (Real-time & FPGA) is used to obtain the acceleration signal data, for fault diagnosis, feature extraction and fault classification. The obtained acceleration and spectrum are used to identify four different conditions of gear: (a) normal healthy gear, (b) gear with pinion defect, (c) gear with wheel defect, (d) gear with both pinion and wheel defects.

Table-2. RMS/Crest factor/Kurtosis Means values.

	RMS	**Crest factor**	**Kurtosis**
Healthy gear	0.48	3.67	3.15
Pinion defect	2.22	8.03	6.88
Wheel defect	3.13	7.97	13.31
Pinion and wheel defect	2.58	8.65	6.88

For isolate gear vibration signature and reduce effect of the bearing signature, all signals are filtered by using a 1KHz-10KHz pass-band filter. To diagnose those

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gears. We consider the evaluation of some temporal parameters like Histogram/RMS/Crest factor/Kurtosis as shown in Table-2 and Figure-3. We see the difference between the four gears in means values and in curves variation of the RMS, Crest factor and Kurtosis parameters. High value and huge variation are correlated with the defect level.

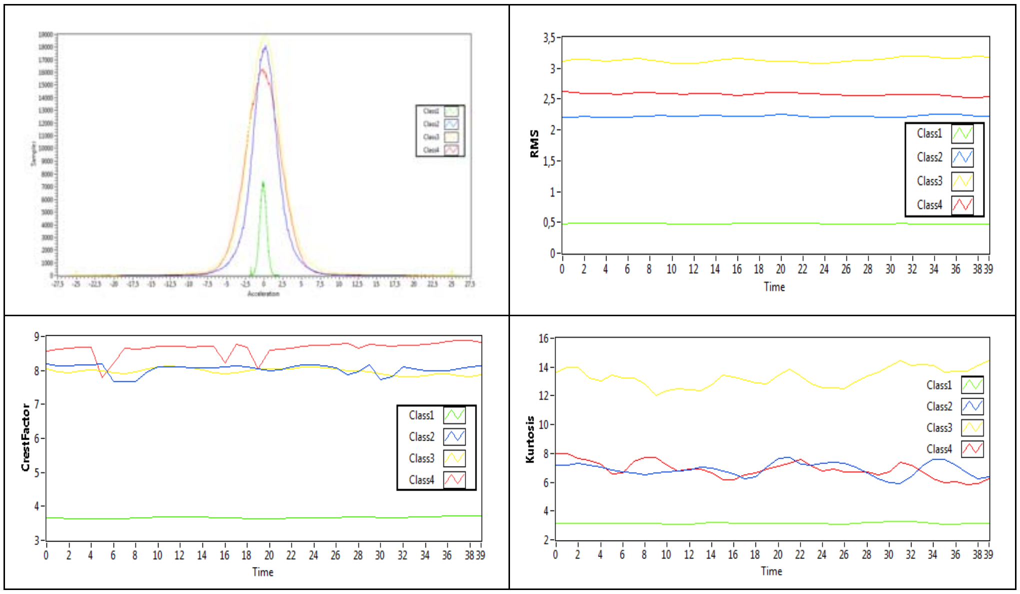

Figure-3. Histogram/ RMS/ Crest factor /Kurtosis, for gear fault class: (a: Green) healthy, (b: Yellow) Gear with pinion defect, (c: Blue) Gear with wheel defect, (d: Red) Gear with pinion/wheel defects.

To diagnose and to identify specified gearbox faults, we use as exposed in Figures (from 4 to 7), FFT spectrum based on radial acceleration and correlated with gear frequency specifications. In the Figure-4 we can see that gear acceleration and spectrum are normal for the first gear condition and indicate a healthy gear, only electrical network frequency 50Hz, gear mesh frequency 118.3Hz and their corresponding harmonics (150Hz, 250Hz, 350Hz…) and (236.6Hz, 354.9Hz, 473.2Hz…) appear with moderates pics and without sidebands around mesh frequency.

The second gear condition, in Figure-5 indicate a gear pinion defect, as appear in the rotational frequency of pinion 1.8Hz (ΔT=0.56sec). With sidebands (1*, 2*, 3*Δf=1.8Hz) around tooth mesh frequency.

Gear acceleration and spectrum, for the third gear condition exposed in Figure-6, are distinct by a wheel defect as appear in in the rotational frequency of wheel 9.1 Hz (ΔT=0.109sec). With sidebands (1*, 2*, 3*Δf=9.1Hz) around mesh frequency.

The forth gear condition is characterized by a serious defect level, see Figure 7, with mixed faults: Pinion defect in 1.8Hz and wheel defect in 9.1Hz. With sidebands (1*, 2*, 3* Δf=1.8Hz) and (1*, 2*, 3*Δf=9.1Hz) around mesh frequency.

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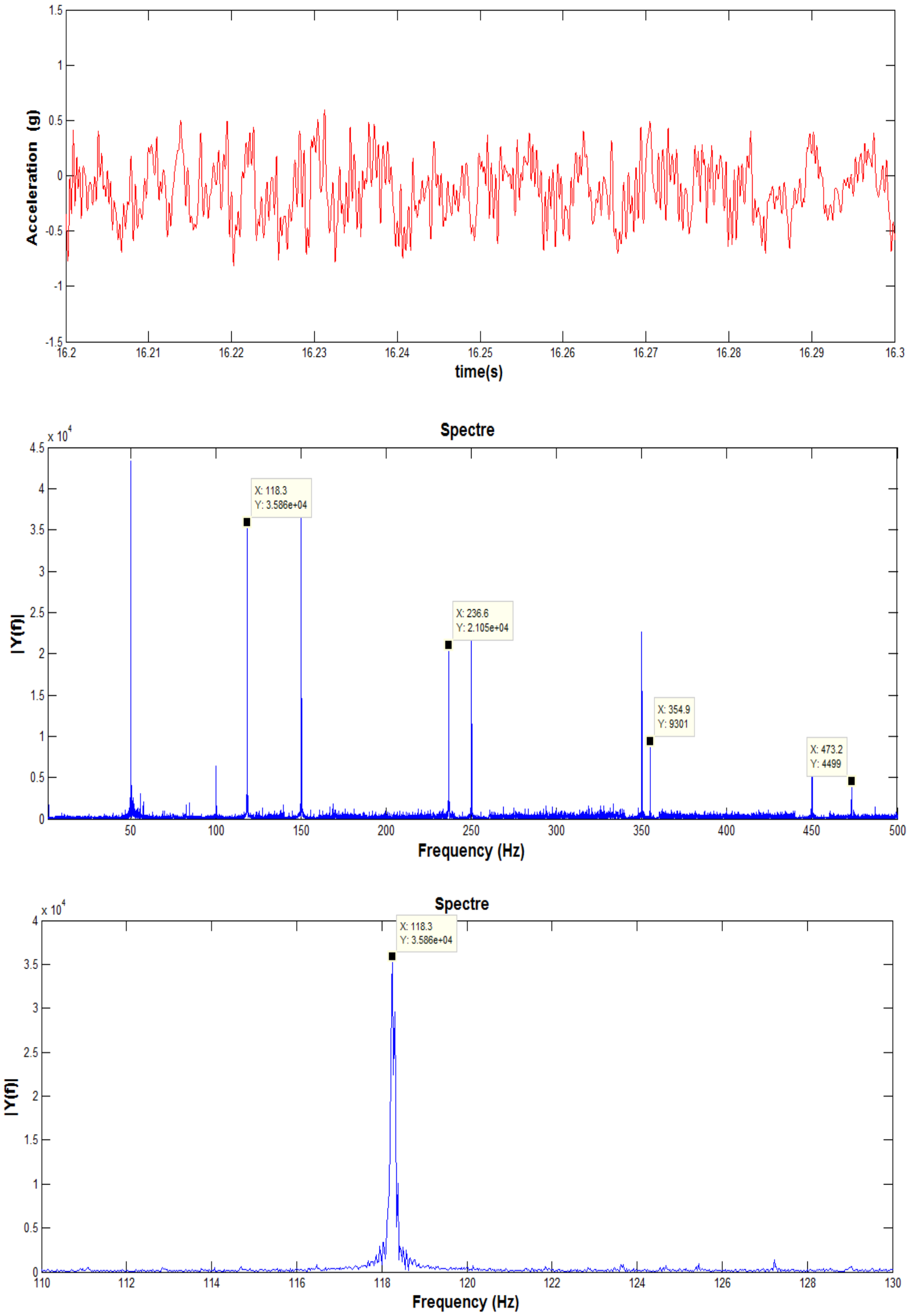

Figure-4. Acceleration signal and its corresponding spectrum for healthy gear.

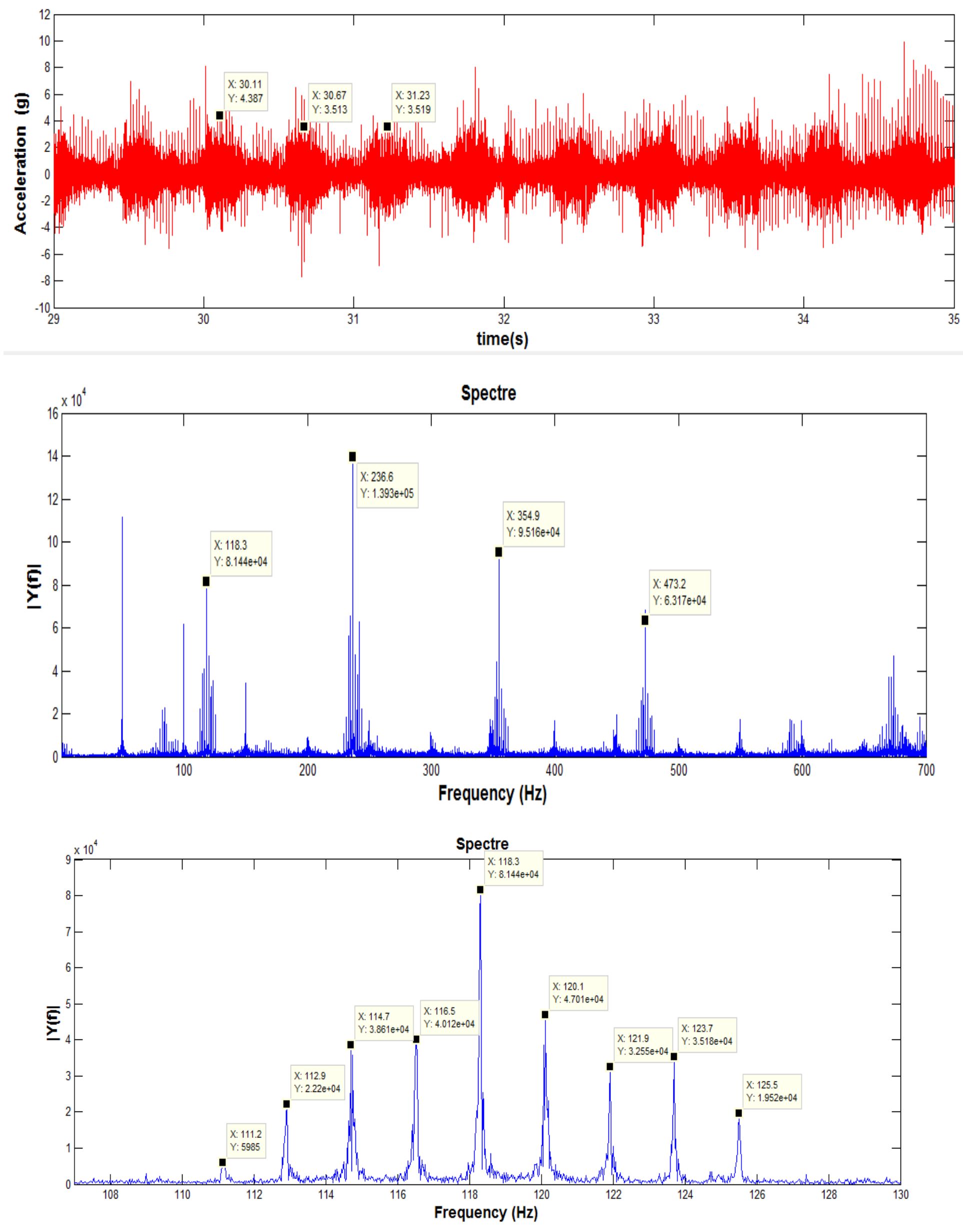

Figure-5. Acceleration signal and its corresponding spectrum for gear pinion defect.

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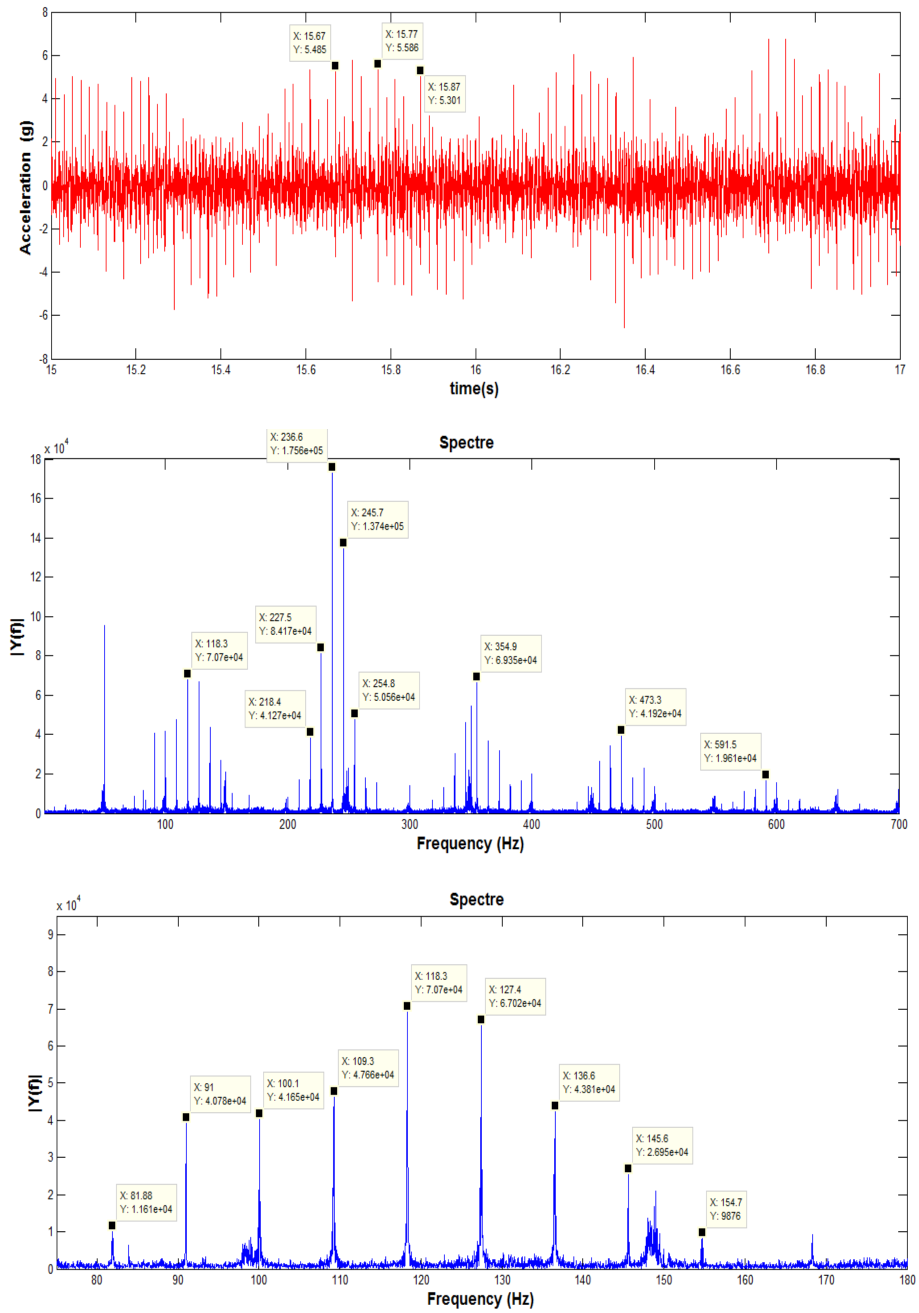

Figure-6. Acceleration signal and its corresponding spectrum for gear wheel defect.

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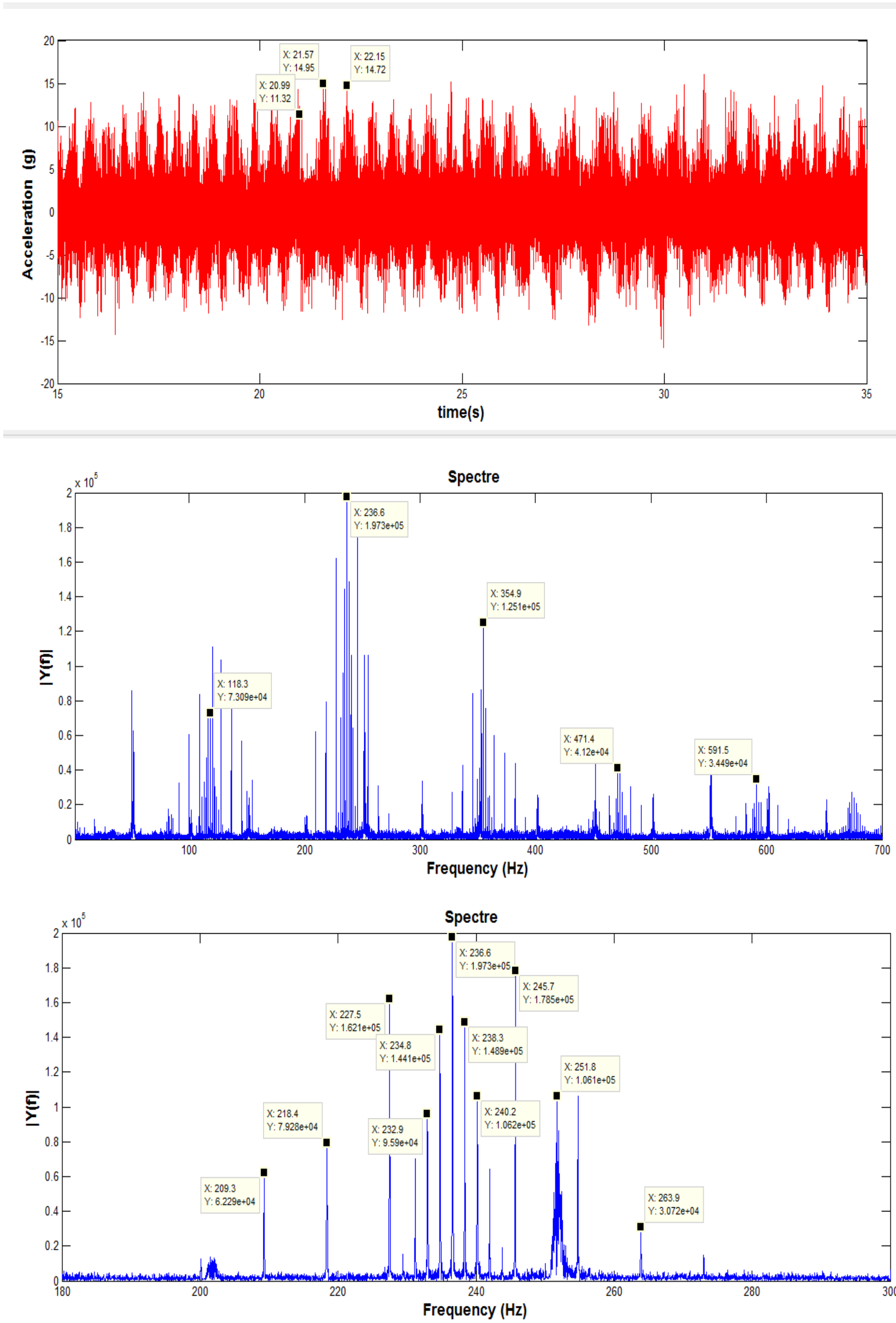

Figure-7. Acceleration signal and its corresponding spectrum for gear pinion/wheel defects.

3. RESULTS AND DISCUSSIONS

To show the effectiveness of the proposed methods, we compare identification and classification scores, based feature extraction (temporal, spectral, alpha stable and wavelet) using the same experimental signal data and processing with KNN and SVM algorithms. Radial accelerometers measurement is organized as 40 sets of data for each gear. We use just a weak amount of training windows: 10% of readings were taken for each gear to calculate the statistical features used as input to classification algorithms.

The recognition identification scores results are detailed in Table-3. It was seen that those scores are mostly excellent: Higher than 99% and up to 99,917% with better scores using SVM classifier. The identification score indicates the similarity between the input and the

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assigned class. It is equal to (1 - d) × 100, where d is the normalized distance between the input vector and the assigned class.

Table-3. Recognition identification score based vibration data.

	KNN	SVM
Temporal	99,097	99,875
Spectral (AS)	99,662	99,889
Spectral (PS)	95,567	99,917
Spectral (PSD)	98,967	99.806
Wavelet	99,212	99,868
αStable	94,272	99,813

Table-4. Recognition classification score based vibration data.

	KNN	SVM
Temporal	95,571	99,097
Spectral (AS)	97,569	99,083
Spectral (PS)	97,222	99,057
Spectral (DSP)	96,554	99,148
Wavelet	96,454	99,104
αStable	99,305	99,135

The classification confidence score indicates the degree to which the assigned class represents the input better than the other classes represent the input. It is equal to (1 - d1/d2) × 100, where d1 is the distance to the closest class, and d2 is the distance to the second closest class. As exposed in Table-4, the SVM classifier offer a very high classification score between 99,057% and 99,148%, the KNN classifier combined with the alpha stable extraction give the highest score 99,305% but it gives, when combined to author extraction methods, acceptable scores between 95, 571% and 97,569%. From the above results, it was inferred that we can improve classification by an appropriate choice of feature extraction and classifier algorithms.

4. CONCLUSIONS

In this paper we study four different gear behaviours, one healthy and three with different defect signs were used. The classification is then obtained using some extraction methods combined with classifiers algorithms based radial vibration acceleration data. The percentage of correct classification was higher than 95, 5% and up to 99, 3% for our proposed feature extraction and the chosen nonlinear classifiers.

REFERENCES

[1] A. Aherwar and M. S. Khalid. 2012. Vibration analysis techniques for gearbox diagnostic: a review. International Journal of Advanced Engineering Technology. 3(2).

[2] A. Malhi and R. X. Gao. 2003. Feature selection for defect classification in machine condition monitoring. in Conference Record IEEE Instrumentation and Measurement Technology Conference. pp. 36-41.

[3] Cerrada M.; Sánchez R.V.; Cabrera D.; Zurita G.; Li C. 2015. Multi-stage feature selection by using genetic algorithms for fault diagnosis in gearboxes based on vibration signal. Sensors. 15, 23903-23926.

[4] Debnath R., Takahidel N., Takahashi H. 2004. A decision based one-against-one method for multi-class support vector machine. Pattern Analysis & Applications. 7, 164-175.

[5] D.P. Jena, S.N. Panigrahi, R. Kumar. 2013. Gear fault identification and localization using analytic wavelet transform of vibration signal. Measurement. 46(3): 1115-1124.

[6] Farag K.Omar & A.M.Gaouda. 2012. Dynamic wavelet-based tool for gearbox diagnosis. Mechanical Systems and Signal Processing. 26: 190-204.

[7] Gang Yu and Ningning Shi. 2012. Gear Fault Signal Modeling and Detection Based on Alpha Stable Distribution. 2012 International Symposium on Instrumentation & Measurement, Sensor Network and Automation (IMSNA).

[8] Gao Z.; Cecati C.; Ding S.X. 2015. A survey of fault diagnosis and fault-tolerant techniques-Part I: Fault diagnosis with model-based and signal-based approaches. IEEE Trans. Ind. Electron. 62, 3757-3767.

[9] Gao Z.; Cecati C.; Ding S.X. 2015. A survey of fault diagnosis and fault-tolerant techniques-Part II: Fault diagnosis with knowledge-based and hybrid/active-based approaches. IEEE Trans. Ind. Electron. 62, 3768-3774.

[10] L.I. Yong-long, S.H.A.O. Ren-ping, X.U.E. Teng. 2010. Gear fault diagnosis based on wavelet and neural network, J. Aerosp. Power. 25(1): 234-240.

[11] Manikandan J., Venkataramani B. 2010. Study and evaluation of a multi-class SVM classifier using

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diminishing learning technique. Neurocomputing. 73, 1676-1685.

[12] Shao Min, Chrysostomos L.N. 1993. Signal processing with fractional lower order moments: stable processes and their applications [J]. Proceedings of the IEEE. 81(7): 986-1010.

[13] Y. Elyassami, K. Benjelloun and M. El Aroussi. 2016. Sleeve Bearing Fault Diagnosis and Classification. 12: 163-170.

[14] Y. Elyassami, K. Benjelloun and M. El Aroussi. 2016. Bearing Fault Diagnosis and Classification Based on KDA and Alpha-Stable Fusion. Contemporary Engineering Sciences. 9(10): 453-465.

[15] Zhou Yuqing, Sun Bingtao, Li Fengping, and Song Wenlei. NC Machine Tools Fault Diagnosis Based on Kernel PCA and k-Nearest Neighbor Using Vibration Signals. Shock and Vibration. 2015(Article ID 139217): 10.

[16] Z. Feng, M. Liang, and F. Chu. 2013. Recent advances in time frequency analysis methods for machinery fault diagnosis: a review with application examples. Mechanical Systems and Signal Processing. 38(1): 165-205.

[17] Zhi Qiang Chen, Chuan Li and René-Vinicio Sanchez. Gearbox Fault Identification and Classification with Convolutional Neural Networks. Shock and Vibration. 2015 (Article ID 390134).