Analyzing Emission Sounds: A way for Early Detection of Bearing Faults in Rotating Machines

Mohamed FEZARI and Zahra TAIF

Abstract— Early detecting faults in main part of Rotating machines (RM) such as Bearing and gears will avoid non programmed stops of production of the machine. Different detection methods using vibration signature analysis, noise signature analysis and lubricant signature analysis were presented in literature reviews. In this paper emitted acoustic signal analysis and processing based on speech recognition features and classifiers were used to detect early faults in REB namely: faults in rolling ball, in inner race, outer race and protecting cage. Commonly used Speech recognition features were selected, also different classifiers were tested: Euclidian distance SVM and GMM then mixed to improve the rate of classifier and make comparison. We obtained as results using MFCC +LPC +SVM as classifier 90%, by including ACP to reduce features and then mixing SVM with GMM we reached the 92% as result. By combining other features kurtosis and Jitter and Shimmer we obtained the 94% in signature faults detection.

Keywords— Fault detection, Acoustic emission, KNN as classifier, ASR features.

I. INTRODUCTION

Bearing fault diagnosis has attracted significant attention from the research and engineering communities over the past decades. Generally, a bearing fault diagnosis process can be decomposed into three steps: data acquisition, feature extraction, and fault detection and classification.

Vibration-based signal analysis in the time-frequency domain has been a major technique for bearing fault diagnosis. Several statistical parameters in the time domain and the frequency domain, such as the root mean square, kurtosis, and skewness, have been shown to be capable of fault detection [1,2]. In [1], nine features in the time domain and seven features in the frequency domain were used for bearing fault detection.

The bearings are one of the targets of this maintenance among the elements composing the rotating system. Acoustic emission (AE) describes the phenomena that result in structure borne elastic waves being generated by rapid energy released from localized sources. AE signal is a high frequency signal, normally over 20 kHz but can be bounded to lower values depending on application. For the high sensitivity, AE becomes more and more popular in condition monitoring of rotating machine. Mba [3] etc. used Acoustic Emission to detect and identify bearing and gearboxes defects. Choudhury and Tandon [4] used Acoustic Emission for detection of defects in ball bearing.

When defects appear on bearings, wide bandwidth periodic AE bursts can be observed. Then the task of bearing fault detection can be performed by finding out whether the AE bursts are periodic and whether it corresponds to one of the characteristic bearing defect frequencies for identifying the type of bearing defect.

Rotary machines are installed in large number of industrial firms. Due to this important number , for the operator, it is necessary to be informed on its mechanical status and early defect in order to take in advance better decision concerning the production and mechanical parts of the machine (when we can change one element at rest time before destruction of the rotary machine). RM (rotating machine) absorbs the energy and transforms it by rotation to anther mechanical energy (rotation to translation). It is composed of rotary part caller 'rotor' and fixed part called 'stator', to ease rotation it needs links and guidance provided by some mechanical elements namely: gears and bearings.

The bearing is the man element to provide link between two subjects in rotation mechanism, it provides relative rotation of elements under load with precision and minimal friction. Most of RM use roller bearing about 40% to 50% of faults are due the bearing defects (ball, outer race and inner race).

II. RELATED WORKS

The main drawback with the application of the AE technique is the attenuation of the signal and as such the AE sensor has to be close to its source. However, it is often practical to place the AE sensor on the non-rotating member of the machine, such as the bearing or gear casing. Therefore, the AE signal originating from the defective component will suffer severe attenuation before reaching the sensor. Typical frequencies associated with AE activity range from 20 kHz to 1 MHz. While vibration analysis on gear fault diagnosis is well established, the application of AE to this field is still in its infancy. In addition, there are limited publications on application of AE to gear fault diagnosis. Siores explored several AE analysis techniques in an attempt to correlate all possible failure modes of a gearbox during its useful life [5].

Based on Singh et al., 1996 work, early detection of gear pitting [6], Tan offered that AE RMS (Root Mean Square) levels from the pinion were linearly correlated to pitting rates;

Mohamed FEZARI Author is with Badji Mokhtar Annaba University Faculty of Engineering Dept. Electronics, BP:12, Annaba, 23000, ALGERIA (e-mail: mouradfezari@yahoo.fr).

Zahra TAIF Author is with is PhD student at Badji Mokhtar Annaba University Faculty of Engineering Dept. Electronics, BP:12, Annaba, 23000, ALGERIA (e-mail: Zahra.taif@yahoo.fr).

ISBN: 978-1-61804-241-5

AE showed better sensitivity than vibration at higher toque level (220Nm) due to fatigue gear testing using spur gears. He made sure that the linear relationship between AE, gearbox running time and pit progression implied that the AE technique offers good potential in prognostic capabilities for monitoring the health of rotating machines [7].

On the other hand, AE signal as a signal processing method was studied using bearing and gearbox. The results of the research in papers [8][9] and [10], the envelope analysis was found to be useful to detect fault in rolling element bearing. The fault detection frequency of bearing can be presented in the power spectrum. Fault gear detection and classification using Wavelet transform was used by applying the signal processing method for the gearboxes [11], but wavelet transforms can give the different results with the envelope analysis. It can be shown the defect frequency, but the efficiency is lower than that of envelope analysis. Thus, the signal processing method for AE signal has not been completed until now, and it must be developed in the future.

In this paper we proceed by using new features and classifier used in speech processing. LFCC and MFCC are very good discriminative features used in automatic speech recognition beside the SI features.

A. Acoustic emission in fault detection

Acoustic emission describes the phenomena that result in structure borne elastic waves being generated by rapid energy released from localized sources. AE signal is a high frequency signal, normally over 20 kHz but can be bounded to lower values depending on application. For the high sensitivity, AE becomes more and more popular in condition monitoring of rotating machine. Mba [12] etc. used Acoustic Emission to detect and identify bearing and gearboxes defects. Choudhury and Tandon [13] used Acoustic Emission for detection of defects in rolling element bearing.

When defects appear on bearings, wide bandwidth periodic AE bursts can be observed. Then the task of bearing fault detection can be performed by finding out whether the AE bursts are periodic and whether it corresponds to one of the characteristic bearing defect frequencies for identifying the type of bearing defect. The de-noising and enhancement of AE signals are of importance for it can reveal the occurrence of these bursts. The reduction of the number of signal coefficients can also greatly reduce the workload of post-analysis; particularly important since the sampling rate for AE signals is usually very high. The AE signals are highly non-stationary for their amplitude and frequency fluctuate. In this case, more adaptive schemes are needed.

B. Rolling Element Bearing in rotating machine

One of the most mechanical components used in rotating machines because of its performance over price, faults in bearing can be generated by a fatigue of material under normal or abnormal functioning conditions. In figure 1, The bearing

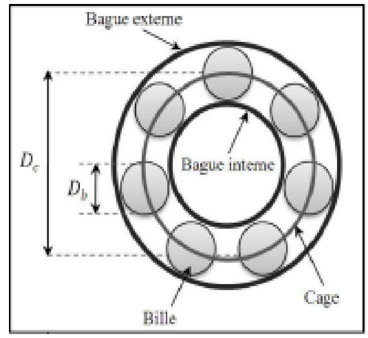

Fig. 1. Rolling element bearing

Bearing can be damaged by external effects:

- External particles contamination of bearing (sand granular, dust..)
- Corrosion engendered by water or acid penetration
- Bad alignment of rotor
- Inadequate lubrification may cause heat and cracks on bearing.
- Electric arc caused by current can affect bearing.
- Bad installation of the bearing

C.Default characteristic frequency

Each fault has its own signature and is characterized by a fundamental frequency which Can be computed from: the structure and dimension and rotation frequency. In vibration analysis, it is possible to observe certain frequencies bands and identify the fault type the characteristic frequencies are expressed as follow:

Outer race fault: $$F_{ex} = \frac{N_b}{2} F_r (1 - \frac{D_b}{D_c} \cos\alpha) \quad (1)$$

Inner Race fault $$F_{in} = \frac{N_b}{2} F_r (1 + \frac{D_b}{D_c} \cos\alpha) \quad (2)$$

Rolling element Fault: $$F_{bi} = \frac{D_c}{2D_b} F_r (1 - (\frac{D_b}{D_c} \cos\alpha)^2) \quad (3)$$

Cage fault : $$F_{ca} = \frac{1}{2} F_r (1 - \frac{D_b}{D_c} \cos\alpha) \quad (4)$$

With F_r is the rotor frequency rotation, D_b diameter of the rolling element and D_c is the diameter of bearing and N_b is the ball number as presented in figure 1. These expressions are well explained in [15].

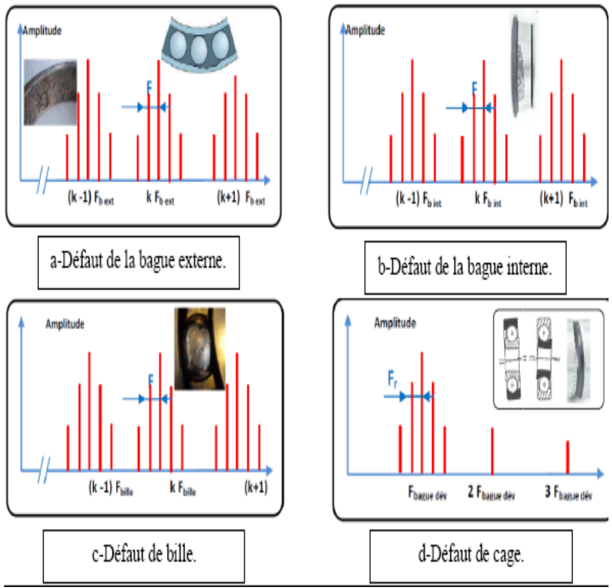

Fig. 2, illustration of some fault in ball bearing

III. ACOUSTIC SIGNAL ANALYSIS

There are different techniques used in acoustic signal analysis in order to detect faults in rolling element bearing, in literature review, most of the work is based on frequency analysis of signal sensed by vibration sensors and processed by AE analysis. To detect faults, FFT to get signal frequencies, RMS (root mean square) to get mean energy, peak to peak to compute maximum amplitude between extreme values, and Kurtosis to compute impulsive corrector of signal it is used to detect chock type faults, these parameters are classified as scalar indicator (SI) features. In Temporal analysis, the samples are processed temporally using crossing zero, extremes and energy envelope. Frequency analysis such as FFT, LPC (linear predictive coefficients) has been used in AE analysis and early work on speech processing.

In our work, we explored classical features and classifiers used in ASR, they gave good results in ASR since they can distinguish between two words close in pronunciation combined with features used in vibration analysiss i.e. SI features. We used Knn and ED as classifiers.

IV. IMPLEMENTATION:

A. Test bench description

The test bench used in experiment is illustrated in fig 3 , it is installed in the laboratory of industrial maintenance and pedagogy at university of 8 Mai Guelma and directed by D. Djabala Abderrazek , this test-bed allow user to create the existing principal faults in ball bearing and to acquire des relative measurements to these different emulated faults. The collected data is done with a microphone (type piezo-electric sensor) installed as near as possible to the noise source (REB), the sensor gets AE and data is stored in hard-disk. The tests need to install and remove respectively 4 type of REB containing the three type of REB fault in (external race, internal race and ball) and one clean REB. To facilitate the experimental set up, only REB belt side is disassembled.

The set up experiment banc used is “SpectratQuest” Banc, it is essentially composed of:

- Rotating asynchronous machine with power 1.5 Kw, synchronism speed 50000 trs/mn, powered by a frequency variation from 0 to 50000 trs/mn that correspond to 0 to 50 Hz frequency variation.
- A Rolling element bearing linked to the motor via elastic coupling
- Microcomputer Type Tochiba, processor i3 (CPU) with 2.27 GHz , RAM: 2 Go, with Sound Card Conexant CX20371.
- Microphone type: FANCONG, FC-350, directivity: noise cancelling, low impedance, sensitivity reduction: within -3dB, and S/N Ratio: more than 36 bD.

Fig. 3 Set up the Test Bench “ Spectra Quest”

V. EXPERIMENTAL PROTOCOL

As illustrated in figure 4, We have to start by collecting data for the training of the developed classifier. We fix the simulation with a clean REB and speed equal to 30 Hz then 40 Hz. With voice toolbox in Matlab, we make 10 recordings of 5 seconds duration and frequency sampling F_s = 10000 Hz, we store files with extension “fileexp_i.wav”.

We do the same work for the three types of faulty REB, the information collected will serve for creating models for four classes and also to test of the application.

Training: this phase is fundamental for supervised classifiers, it plays an important role in classification success, it depends on type of data and also in the quantity of collected data, it constitutes the knowledge to learn for better generalization and representation of different classes. It is composed of the following steps: data collection, data processing, features extraction, models construction.

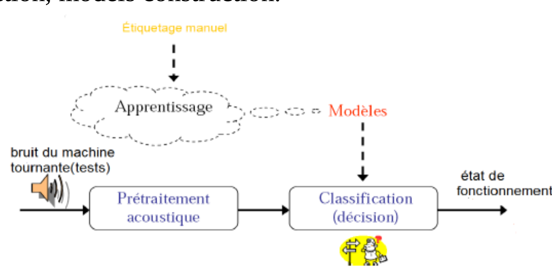

Fig. 4 fault monitoring flowchart.

The data collected from microphone is acoustically pre-processed using: hamming window where each segment of large 80ms with shifting in time of 30 ms, parameterization where the samples are processed and represented by a reduced quantity of information using three methods in our case (scalar indicator SI, linear predictive Coefficients LPC and Mel frequency Cepstral Coefficients MFCC), MFCC and LPC are computed using the bloc diagram in figure 5, more details on [14] .

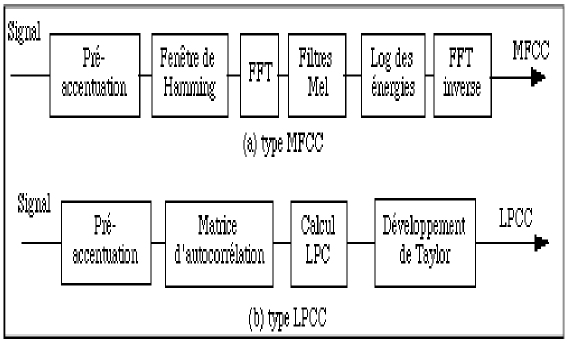

Fig. 5. Bloc diagram of MFCC and LPC computation.

In SI, we compute the following parameters: mean, Kurtosis which is used to detect shock type fault based on impulsive character of the signal, Energy, RMS where peak to peak and maximum amplitude between extreme values is computed, and variance.

For LPC we have taken the 10 first parameters and the 12 first parameters for the MFCC [14].

Model design and classification: we have used two techniques to classify data, and we tested for each type of feature the two classifiers, Euclidian distance and KNN (K nearest neighbor) despite it is a non parametric method.

Euclidian distance is a classic method to evaluate the proximity of two vectors of same dimension. Let Xj=[xj1,xj2,xj3,…xjn] be the vector of a class j and Y=[y1,y2,…..,yn] the vector corresponding to the test signal, the Euclidian distance between the two vector X and Y is defined by the equation:

$$Dj = \sqrt{\sum_{i=1}^{n}(xji - yi)^2} \quad (5)$$

The minimum value of the distance D for j=1...m, where m is the number of classes, represents the class of the test signal.

Knn (K nearest neighbor): this technique uses as input a matrix X_{app} coordinates of points of characteristic vector for each signal, Y_{app} Class vector for each of training point, X_{test} matrix of points coordinates to classify, and K the number of near neighbor to take in consideration.

As output, we have Y_{pred} a class vector for the values to classify.

This function Knn allows classifying the K nearest neighbors, it computes the distance matrix between the test points (values) and training values, for each test point we get all distances with training points, and then we keep k nearest training points and affect the test point to this class. We do the same thing for all test points before returning the class vector for values to classify.

Techniques for dimension reduction: we used CPA (Corposant Principal Analysis) to reduce the number of features. The following program code presents the computation of PCA for healthy, outer race fault, inner race fault and ball bearing fault using ACP1function.

```
function [wreduit]=acp1(W)
W1=W'; mx=mean(W1);
stdx=std(W1);ax=zeros(size(W1));
[r1,c1]=size(W1);
for i=1:r1
ax(i,:)=(W1(i,:)-mx)./stdx;
end
cov=ax'*ax/(r1-1);
[v,d]=eig(cov); d=diag(d);
[a,t1]=sort(d);
t1=t1(c1:-1:1);
d=d(t1); v=v(:,t1); t2=ax*v;
xe=ax*v(:,1:4)*v(:,1:4)';
s=t1(1:4,:);
wreduit=W1(:,t1(1:4,:))
end
[S] = acp1(Ws);      { for healthy motor}
[BX] = acp1(Wbx); { fault in outer race bearing}
[BI] = acp1(Wbi);    { fault in inner race bearing}
[B] = acp1(Wb);      { fault in baal bearing}
```

The acoustic segment vector is represented by many features: 12 MFCC, 10 PLC, energy and SI features. The principal axes are determined by data covariance matrix, the directions to maximize the variability are determined due to proper values and associated proper values. At this stage, the new representation space has the same dimension as initial space, this new space ease the statistic de-correlation among axes. In order to reduce the acoustic segment vector dimension only the axes comporting maximum information (selected by large proper value) are conserved.

VI. TESTS AND RESULTS OF TWO SCENARIOS

First scenario, we used ED as classifier with different features , the results are presented in table 1.

Regarding obtained results in table 1, temporal features presented by SI lack of precision for bearing faults detection, however they give an acceptable result concerning gearbox fault detection (in our case the used gear has 3 broken teethes) .

LPC and MFCC separately are compared and it is obvious that MFCC with 12 coefficients is better than LPC with 10 coefficients, but ball bearing degradation can be classified as inner race fault which explains the 50% and 75% in LPC and MFCC respectively.

Table 1. Fault detection results using ED classifier.

Test performance	Scalar Indic	LPC	MFCC	SI+MFCC	SI+MFCC+ LPC	SI+MFCC+PCA
Healthy	**75 %**	**90 %**	**92 %**	**95%**	**95%**	**98%**
Outer race fault	**50 %**	**92 %**	**96 %**	**96%**	**96%**	**97.5%**
Inner race fault	**25 %**	**90 %**	**95 %**	**97%**	**97%**	**98%**

Ball fault	**75 %**	**50 %**	**94 %**	**98%**	**98%**	**98.5%**
gearbox	**90 %**	**90 %**	**95 %**	**98%**	**98%**	**99%**

By inserting temporal features SI, we did not see any improvement in result at columns 5 and 6, this is due to redundancy of features. Thus to improve the results we added features redactor algorithm PCA and results are in column 7.
Second scenario, we used KNN as classifier, the obtained results are presented in table 2.

Table 2. Fault detection results using KNN classifier.

Test performance	Scalar Indic	LPC	MFCC	SI+MFCC	SI+MFCC+ LPC	SI+MFCC+PCA
Healthy	**80 %**	**93 %**	**95 %**	**97%**	**97%**	**98.2%**
Outer race fault	**50 %**	**93 %**	**96 %**	**96.5%**	**97%**	**97.8%**
Inner race fault	**85 %**	**91 %**	**96 %**	**98%**	**98%**	**35%**
Ball fault	**25 %**	**25 %**	**97 %**	**75%**	**98%**	**98.75%**
gearbox	**50 %**	**94 %**	**96 %**	**98%**	**99%**	**99%**

Based on results in table 2, we have got bad results concerning gearbox faults, ball and outer race faults using just Si features.
KNN gave better results using LPC and MFCC compared to ED, except for ball bearing faults the result are less than 50% due to confusion in classification with inner and outer race faults class. Good results are reached by combining Si, MFCC and LPC as features as seen in column 6. This takes more time in classification due to more data to process, by inserting PCA algorithm in order to reduce the features we observed a decrease to 80% (due to 0% in ball bearing faults), this might be due to loss of some discriminate features with PCA.
We have observed that some values in tables 1 and 2 can be influenced by:
Number of features (including first and second derivative of MFCC), segment window dimension, number of training files for different faults, reducing number of classes (i.e : gearbox faults and bearing faults).

VII. CONCLUSION

In this work, a test bench for asynchronous motor has been used to validate the acoustic emission analysis, based on speech processing features, produced by ball bearing defaults. We have used LPC and MFCC including SI as features then we used two classifiers ED and KNN. Seven acoustic features (SI) are added to classical features to improve the rate of classification for common faults in asynchronous motor (bearing and gearbox faults). We have used five classes (three for bearing faults one for gearbox and one for healthy motor). The selected classifiers have shown their aptitude to classify datasets for different type of indicators. Better results for ED are obtained using MFCC and SI features processed by PCA algorithm and the best results for KNN is reached using MFCC as feature without need to PCA. Computation time is reduced in the KNN case, PCA gave better results even if there is a computation time added in training phase. In future work, it would interesting to test the habitation GMM/HMM [16] as classifier and to process other type of faults within the RM [17].

ACKNOWLEDGMENT

We would like to thanks Professor Hassan NOURI from University of West England for his contribution to this work by allowing us to do training in his laboratory at UWE. Bristol, UK.

REFERENCES

[1] Xu, Z.; Xuan, J., Shi, T.; Wu, B.; Hu, Y. A novel fault diagnosis method of bearing based on improved fuzzy ARTMAP and modified distance discriminant technique. Expert Syst. Appl. **2009**, 36, 11801–11807. 2009

[2] Li, B.; Zhang, P.L.; Wang, Z.J.; Mi, S.S.; Liu, D.S. A weighted multi-scale morphological gradient filter for rolling element bearing fault detection. ISA Transactions **2011**, 50, 599–608.2011

[3] D. Mba, "Prognostic opportunities offered by acoustic emission for monitoring bearings and gearboxes, " 12th International Congress on Sound and Vibration, 2005.

[4] A. Choudhury, N. Tandon,, "Application of acoustic emission technique for the detection of defects in rolling element bearing," Tribology International 33, 39-45.2000.

[5] Siores, E. & Negro, A.A. "Condition monitoring of a gear box using acoustic emission Testing", Material Evaluation, Vol. 55, No. 2, (February 1997), pp.183-187, ISSN 00255327.1997.

[6] Singh, A., Houser, D. R. & Vijayakar, S. (1996). "Early detection of gear pitting", American Society of Mechanical Engineers, Vol. 88, pp.673-678, ISSN 15214613.1996.

[7] Yang, Y., Yu, D. & Cheng, J. « A fault diagnosis approach for roller bearing based on IMF envelope spectrum and SVM", Measurement: Journal of the International Measurement Confederation, Vol. 40, No. 9-10, (November 2007), pp.943-950, ISSN 0263-2231, 2007.

[8] Sheen, Y.T. "An envelope detection method based on the first-vibration-mode of bearing vibration", Measurement: Journal of the International Measurement Confederation, Vol. 41, No. 7, (August 2008), pp.797-809, ISSN 0263-2231, 2008.

[9] Sheen, Y.T. "An envelope analysis based on the resonance modes of the mechanical system for the bearing defect diagnosis", Measurement: Journal of the International Measurement Confederation, Vol. 43, No. 7, (August 2010), pp.912-934, ISSN 0263-2241, 2010.

[10] Wu, J.D., Hsu, C.C. & Wu, G.Z. "Fault gear identification and classification using discrete wavelet transform and adaptive neuro-fuzzy inference", Expert Systems with Applications, Vol. 36, No. 3, (April 2009), pp.6244-6255, ISSN 0957-4174, 2009.

[11] N. Tandon, A. Choudhury, "A review of vibration and acoustic measurement methods for the detection of defects in rolling element bearings," Tribology International 32, 469-480, 1999.

[12] D. Mba, “Prognostic opportunities offered by acoustic emission for monitoring bearings and gearboxes, ” 12th International Congress on Sound and Vibration, 2005.

[13] A. Choudhury, N. Tandon,, “Application of acoustic emission technique for the detection of defects in rolling element bearing,” Tribology International 33, 39-45, 2000.

[14] M. Fezari and M. Bedda, “Hybrid technique to enhance voice command system for a wheelchair”, in proceedings of Arab Conference on Information Technology ACIT’05, Jordan, 2005.

[15] Taif Zahra, Mebarki S., “ Identification et Classification des defaults dans les machines tournante par etude fréquantielle des emissions sonores », Master thesis directed by M. FEZARI at dept. Electronics UBMA, 2011.

[16] Mohamed FEZARI, Fethi AMARA, ”Voice Disorder Detection based on Automatic Speaker Identification techniques” , ICIT 2013, Amman, Jordan, 2013.

[17] Tan, C.K., Irving, P. & Mba, D. , “A comparative experimental study on the diagnostic and prognostic capabilities of acoustics emission, vibration and spectrometric oil analysis for spur gears”, Mechanical Systems and Signal Processing, Vol. 21, No. 1, (January 2007), pp.208-233, ISSN 0888-3270, 2007.

M. FEZARI (MS’87–PhD2006 and HDR-2010) is Associate Professor At Badji Mokhtar Annaba University Faculty of Engineering dept. Electronics; He is recently member of TPC in many conferences, he has many published proceedings and publications in different journals. His research interests are: signal processing, speech processing, HMI and WSN.