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TIME DOMAIN BEARING DEFECTS DIAGNOSIS BASED ON GAUSSIAN FILTERING AND FUZZY LOGIC

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Abstract: *On this paper a novel bearing defects diagnosis method is introduced. This diagnosis method is based on time domain signal processing first step being the Gaussian filtering.*
The reason of this filtering is the detection of the shock pulses generated by bearing defects. The diagnosis is done based one the detected defects periods which are used as inputs for a fuzzy classifier that provide defect alerts for each kind of bearing localize defect.
Key words: *bearing defects, Gaussian filtering, fuzzy classification.*

1. INTRODUCTION

The bearings are considered important components in almost mechanical system having a roll as connection components.

This paper proposes a method of diagnosis the bearing defects based on defects shock pulsed detection using Gaussian filtering. As soon as these pulses are detected, the periods between consecutive pulses are measured in order to detect defects periods. All signal processing tools used to diagnose bearing defects by this proposed method are done in time domain.

The diagnosis of the proposed method is done based one the detected defects periods which are used as inputs for a fuzzy classifier.

The fuzzy logic was used in other proposed bearing diagnosis methods [1], but the input variables are mainly represented by the defect frequencies.

The Gaussian filtering is not very used in bearing defects diagnosis, some of the few researches being related to envelope detection ability of the Gaussian filtering [2, 3].

This paper is organized as follow. Section 2 represents a theoretical review of Gaussian filtering; section 3 presents the bearing defects periods and the experimental data used on this research; section 4 illustrates the detailed formulation of the proposed method; section V is dedicated to evaluation of the proposed method describing the results obtained applying this method; finally, the conclusions and the references list are completing the paper.

2. THEORETICAL FRAMEWORK

2.1 Gaussian Filtering

The Gaussian filter is obtained from the convolution of the input signal with a low pass Gaussian filter.

$$g(t) = G_\sigma * x(t) \qquad (1)$$

where G_σ is the Gaussian kernel of standard deviation (Gaussian half-width) σ:

$$G_\sigma(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-x^2/2\sigma^2} \qquad (2)$$

σ^2 is the variance parameter

The discrete representation [4] which is use in practice to compute the Gaussian filtering as a convolution is implemented as a finite sum as it follows:

$$g[x] = \sum_{k=-K_s/2}^{K_s/2} f[x-k]G_\sigma[k] \text{, for any } x \qquad (3)$$

where K_s is the kernel size, g is the discrete filtered output, $G_\sigma[k]$ is the discrete representation of the Gaussian kernel

The Gaussian filtering is configurable based on two parameters: the kernel size K_s and the variance parameter σ^2. For a bigger K_s you can get a better accuracy but much more computation time.

Table 1

Gaussian filters configurations

Configuration	K_s	σ^2
Gaussian filtering 1	41	28
Gaussian filtering 2	201	370

Fig. 1 illustrates the results of applying these two configurations of Gaussian filtering to a vibration signal obtained from a defect bearing.

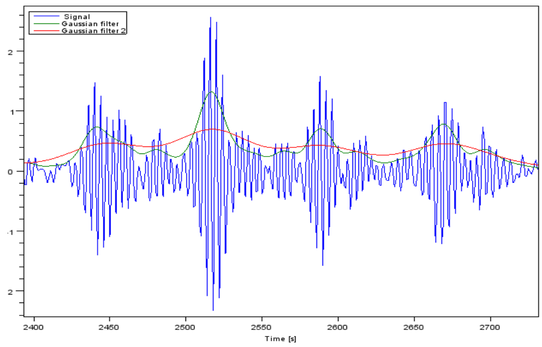

Fig. 1. Gaussian filtering of the signal

3. BEARING DEFECTS PERIODS AND USED EXPERIOMENTAL DATA

The time periods between of the impact shock pulses generated on the vibration signal by the collision of the defect with bearing components depends of the place of the defect on bearing components. The defects specific periods that allow us to identify the defects place are computed as follows:

$$T_{out} = 2 \Big/ n_b f_r \left[1 - \frac{D_b}{D_p}\cos\alpha\right] \quad (4)$$

$$T_{in} = 2 \Big/ n_b f_r \left[1 + \frac{D_b}{D_p}\cos\alpha\right] \quad (5)$$

$$T_b = 2D_b \Big/ f_r D_p \left[1 - \left(\frac{D_b}{D_p}\cos\alpha\right)^2\right] \quad (6)$$

T_{out} - the ball pass period on the outer race

T_{in} - the ball pass period on the inner race

T_b - the ball rotation period (spin rotation)

where n_b is the number of rolling elements, D_b and D_p are the ball diameter and respectively the average (pitch) diameter and α is the contact angle. f_r is the frequency of relative rotation between races, if a general configuration where both rings may rotate is assumed. The bearing structural parameters are presented on the Fig. 2.

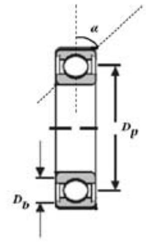

Fig. 2. Bearing parameters

All the vibration data used on this research were obtained from the "Bearing Data Center (B.D.C.)" [5].

The experimental signals were obtained by capturing the vibrations generated by bearings with localized defects using accelerometers. Experimental data were collected with a rate of 12000 samples per second (0.0000833 s sampling period).

The experimental data were obtained using a SKF 6205 bearing. Table 2 and Table 3 present the parameters of bearings used on experimental vibration data capturing process and respectively the defects periods corresponding to these bearing parameters.

The shaft rotation frequency used for experiments was 1750 RPM (f_r =29.166667 Hz) for all experiments. On this research the out ring of the bearing was fixed, so the frequency of relative rotation between races (f_r) was the same with the motor rotation frequency.

Table 2

Bearing parameters

parameters	6205-2RS JEM SKF
nb	9
Dout	52 mm
Din	25 mm
w	15 mm
Db	7.94004 mm = 0.00794004 m
Dp	39.0398 mm = 0.0390398 m

Table 3

Defects periods of bearing

Periods type	Defect periods values
Tin	0.0063314 s
Tout	0.0095642 s
Tb	

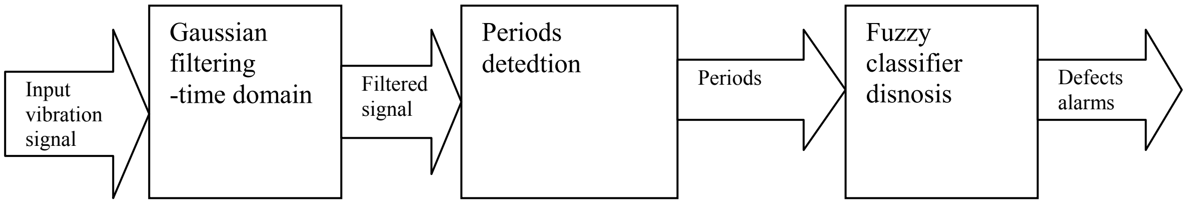

Fig. 3. Block diagram of the proposed diagnosis method

4. PROPOSED DIAGNOSIS METHOD FORMULATION

The proposed diagnosis method by this paper represents a bearing diagnosis method which works in time domain and is based on the Gaussian filtering of the input vibration signal and a Fuzzy logic classification. The Fig. 3 illustrates the block diagram of the proposed method and is composed from tree based processing blocks.

The first step is represented by the Gaussian filtering of the input vibration signal. The result of the filtering process is a signal which presents Gaussian like peeks, corresponding to shock pulses generated by the collision of the defect component of the bearing with another component. The new signal obtained after the Gaussian filtering presents the next characteristics:

- The Gaussian peeks can be very easy detected (enhanced) on the signal wave because the peek are detected as local maximums.
- The time periods between two Gaussian peeks (between two local peeks) are relative constant time periods which are the repeatedly detected as the bearing defect periods. In case of detected periods bigger than bearing defects periods, these periods have usually the value double (or multiple) of the defect periods because these bigger periods can appear because of one ore more undetected shock pulse on the shock pulses detection process (filtering). This shock pulsed missing behavior is happen because of some shock pulsed with low amplitude ore because of the noise. The percent of missed shock pulsed can be influenced by the values of Gaussian filtering parameters.

It is also possible to be detected fake Gaussian peeks (false positive) which don't corresponds to any real shock pulse, and appear because of noise or any other perturbation from the mechanical system.

Now, the question is how to choose the Gaussian filtering parameters to obtain good shock pulses detection results. On this research we used for all Gaussian filtering the next parameters:

The last step of the proposed method is the Fuzzy logic classifier which realizes the defects diagnose deciding what kind of defect is present if it is present.

The evaluation of this proposed a diagnosis method was made using three sets of data from different defect bearings outer race defect, inner race defect and ball defect. The Gaussian filtering results and all the detected periods for all four sets of vibration data are illustrated on the Fig. 4-9

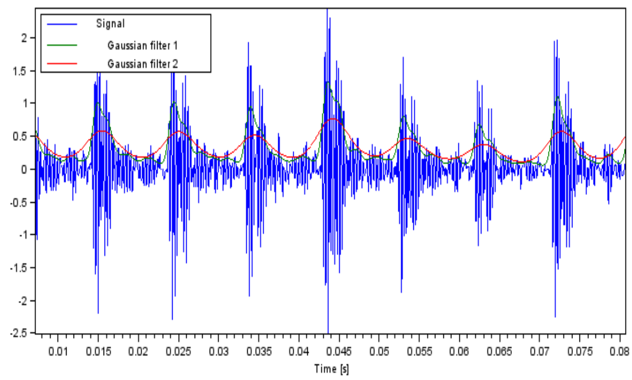

Fig. 4. Gaussian filtering of outer race bearing defect vibration data

The membership functions used on this research for fuzzy classifier are trapezoidal type functions, as we can see on the Fig. 10-13.

The fuzzy logic implementation was done using the tool Scilab Fuzzy Logic Toolbox [6], a plug-in for Scilab environment [7].

The fuzzy rules used for this diagnosis technique re presented on Table 5. The output surfaces for each output variable obtained based fuzzy rules for each output variable are illustrated by the Figures 12-14.

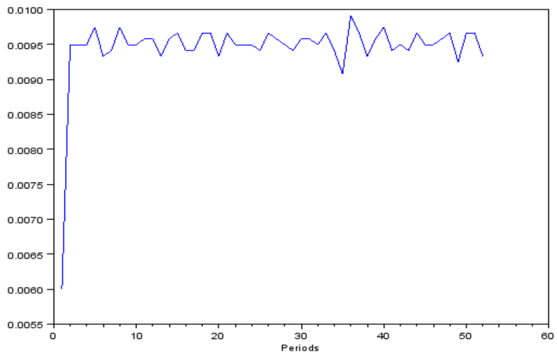

Fig. 5. Periods values obtained for outer race bearing defect vibration data

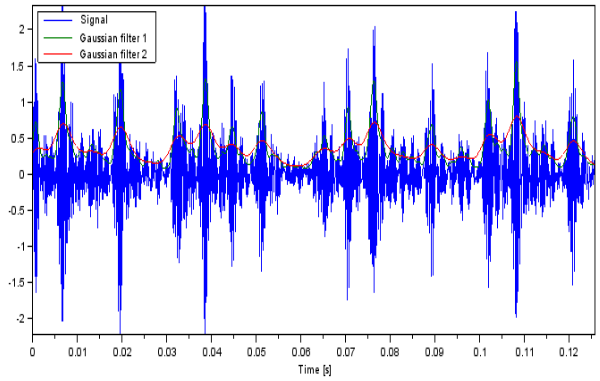

Fig. 6. Gaussian filtering of inner race bearing defect vibration data

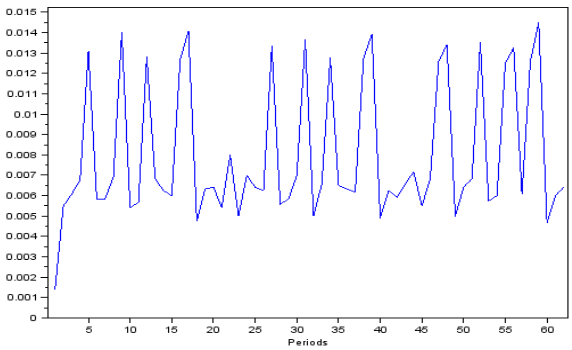

Fig. 7. Periods values obtained for inner race bearing defect vibration data

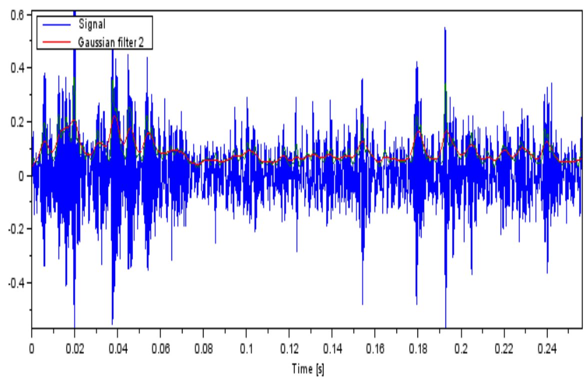

Fig. 8. Gaussian filtering of ball bearing defect vibration data

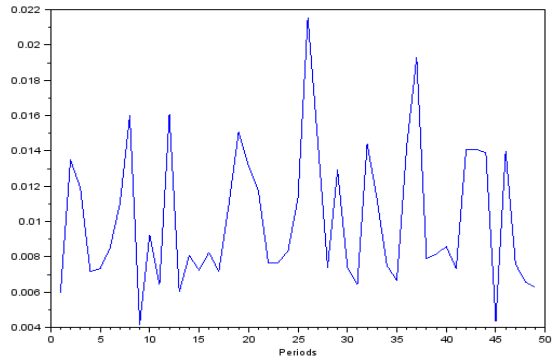

Fig. 9. Periods values obtained for ball bearing defect vibration data

Table 4

Input variables

Variable name	Description
periodsIn	the number of periods which have approximately the same value with Tin
periodsIn2	the number of periods which have approximately the same value with double of Tin
periodsOut	the number of periods which have approximately the same value with Tout
periodsOut2	the number of periods which have approximately the same value with double of Tout
periodsB	the number of periods which have approximately the same value with Tb
periodsB2	the number of periods which have approximately the same value with double of Tb
periodsBHalf	the number of periods which have approximately the same value with half of Tb

Table 5

Output variables

Variable name	Description
defectIn	Indicates the presence of defect on the inner race of the bearing
defectOut	Indicates the presence of defect on the outer race of the bearing
defectB	Indicates the presence of defect on one of the ball of the bearing

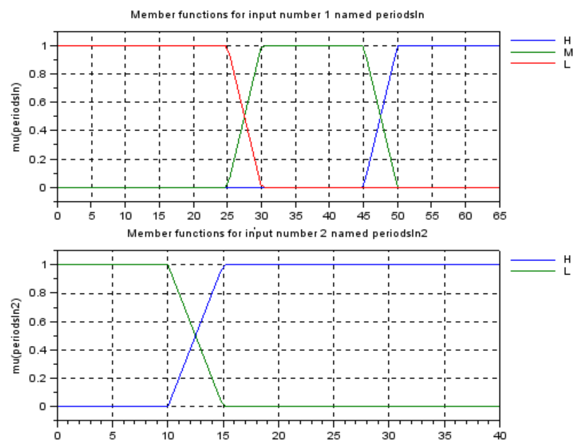

Fig. 10. Membership functions of input variables periodsIn and periodsIn2

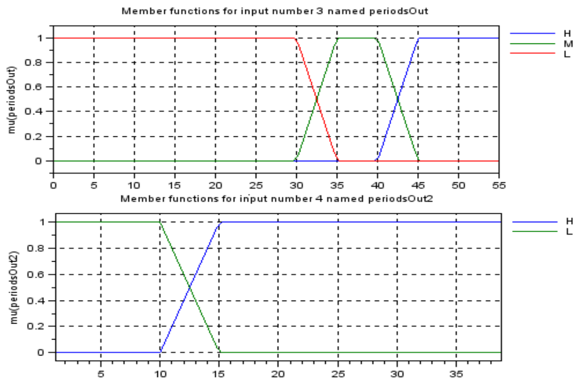

Fig. 11. Membership functions of input variables periodsOut and periodsOut2

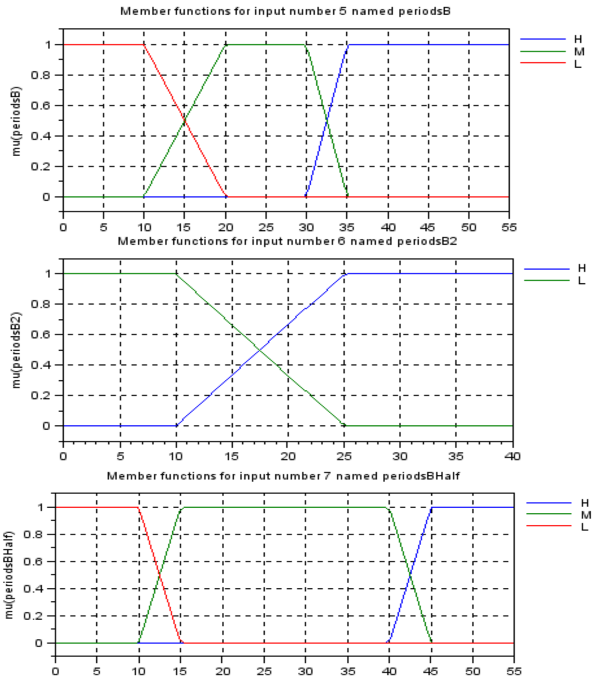

Fig. 12. Membership functions of input variables periodsB, periodsB2 and periodsBHalf

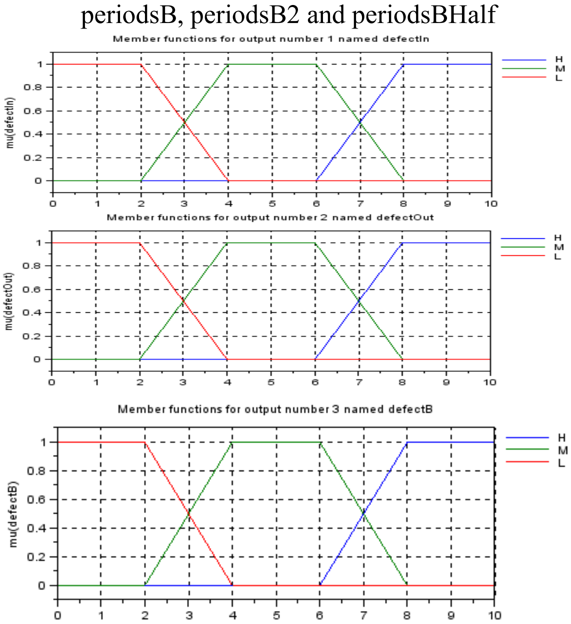

Fig. 13. Membership functions of output variables defectIn, defectOut and defectB

Table 6

If-Than rules (rules matrix)

IF							THAN		
I1	I2	I3	I4	I5	I6	I7	O1	O2	O3
H	-	L	L	L	L	L	H	L	L
M	L	L	L	L	L	L	M	L	L
L	-	L	L	L	L	L	L	L	L
M	H	L	L	L	L	L	H	L	L
L	L	H	-	L	L	L	L	H	L
L	L	M	L	L	L	L	L	M	L
L	L	L	-	L	L	L	L	L	L
L	L	M	H	L	L	L	L	H	L
L	L	L	L	H	-	-	L	L	H
L	L	L	L	M	L	L	L	L	M
L	L	L	L	L	-	-	L	L	L
L	L	L	L	M	L	M	L	L	H
L	L	L	L	M	H	L	L	L	H
L	L	L	L	-	-	H	L	L	L
M	**H**	**L**	**L**	**M**	**L**	**L**	**H**	**L**	**L**

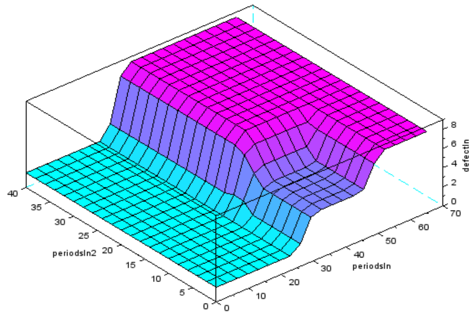

Fig. 14. Output surface of defectIn variable

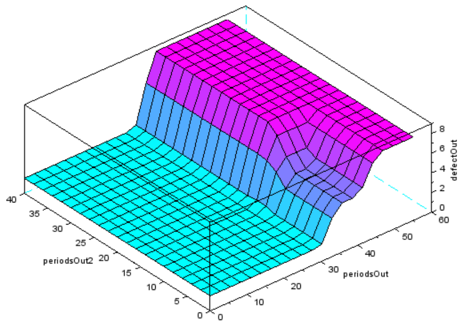

Fig. 15. Output surface of defectOut variable

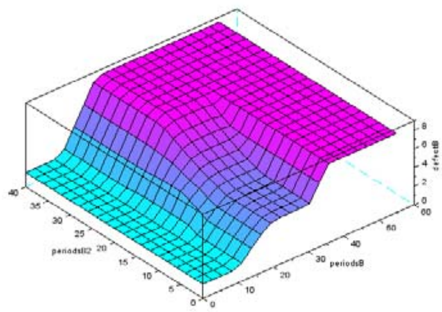

Fig. 16. Output surface of defectB variable

5. RESULTS ANALYSIS

Analyzing the diagnosis results of all kinds of localized defects of bearing presented on Table 7.

Table 7

Diagnosis results

Defect type	I1	I2	I3	I4	I5	I6	I7	O2	O2	O3
Inner race	31	16	0	0	18	10	0	8.470	1.529	1.529
Outer race	1	0	51	0	0	0	0	1.529	8.470	1.529
Ball	7	11	1	1	19	11	1	1.529	1.529	4.917

In the Table 7 we can observe that all the defect types were correct diagnosis, but the outer race and inner race defects were clearly indicated comparing with ball defect which was detected as a medium severity.

6. CONCLUSION

Even there are not present on the literature this kind of time domain diagnosis methods based on the defects periods analysis, we proposed this bearing diagnosis method because we considered that the defects periods is matching with fuzzy classification.

This research can continue by validating this proposed method with more experimental vibration date.

This proposed diagnosis method is suitable to be implemented on embedded hardware systems with minimal resources requirements.

7. ACKNOWLEDGMENTS

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Diagnoza defectelor rulmenților în domeniul timp bazată pe filtrarea Gaussiană şi logica Fuzzy

Rezumat: In lucrare se prezintă modul de diagnosticare a defectelor rulmenților prin filtrarea Gaussiană şi prin logica Fuzzy. Se detectează, astfel, defectele apărute datorită şocurilor din rulment. Metodele de investigare sunt apliocate pentru prima dată în această direcție de studiu.

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