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A synchronous filter for gear vibration monitoring using computational intelligence

by

Lungile Mndileki Zanoxolo Mdlazi

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Lungile Mndileki Zanoxolo Mdlazi

Supervisor	:	Prof. P.S. Heyns
Co-supervisors	:	Prof. T. Marwala
		Mr C.J. Stander
Department	:	Mechanical and Aeronautical Engineering
Degree	:	M.Eng.

Summary

Interaction of various components in rotating machinery like gearboxes may generate excitation forces at various frequencies. These frequencies may sometimes overlap with the frequencies of the forces generated by other components in the system. Conventional vibration spectrum analysis does not attenuate noise and spectral frequency band overlapping, which in many applications masks the changes in the structural response caused by the deterioration of certain components in the machine.

This problem is overcome by the use of time domain averaging (synchronous averaging). In time domain averaging, the vibration signal is sampled at a frequency that is synchronised with the rotation of the gear of interest and the samples obtained for each singular position of the gear are ensemble-averaged. When sufficient averages are taken, all the vibration from the gearbox, which is asynchronous with the vibration of the gear, is attenuated. The resulting time synchronously averaged signal obtained through this process indicates the vibration produced during one rotation of the monitored gear. This direct time domain averaging process essentially acts as a broadband noise synchronous filter, which filters out the frequency content that is asynchronous with the vibration of the gear of interest provided that enough averages are taken. The time domain averaging procedure requires an enormous amount of vibration data to execute, making it very difficult to develop online gearbox condition monitoring systems that make use of time domain averaging to enhance their diagnostic capabilities since data acquisition and analysis cannot be done simultaneously.

The objective of this research was to develop a more efficient way for calculating the time domain average of a gear vibration signal. A study of Artificial Neural Networks (ANNs) and Support Vector Machines (SVMs) was conducted to assess their suitability for use in time domain averaging. Two time domain averaging models that use ANNs and SVMs were developed. Model 1 uses a single feedforward network configuration to map the input which are rotation synchronised gear vibration signals to the output which is the time domain average of the gear vibration signal, using only a section of the input space. Model 2 operates in two stages. In the first stage, it uses a feedforward network to predict the instantaneous time domain average of the gear vibration after 10 inputs (10 rotation synchronised gear vibration signals) to predict the instantaneous average of the gear rotation. The outputs from the first stage are used as inputs to the second stage, where a second feedforward network is used to predict the time domain average of the entire vibration signal.

When ANNs and SVMs were implemented, the results indicated that the amount of gear vibration data that is required to calculate the time domain average using Model 1 can be reduced by 75 percent and the amount of gear vibration data that needs to be stored in the data acquisition system when Model 2 is used can be reduced by 83 percent.

Keywords: Artificial Neural Networks, Time Domain Averaging, Synchronous average, Multi-layer, Perceptron, Radial Basis Function, Support Vector Machines, Gearbox and Vibration

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Nomenclature

Symbol	**Description**
$\lVert \mathrm{x} - \mathrm{x}^{n} \rVert$	Euclidian distance between **x** and **x**^{n}
$\mathbf{\Phi}$	Square matrix with elements $\phi_{nn} = \phi(\lVert \mathrm{x} - \mathrm{x}^{n} \rVert)$
$\mathbf{\Phi}^{\dagger}$	Pseudo inverse
$\xi_i^- \xi_i^+$	Slack parameter presenting the lower and upper constraints
$R[f]$	Risk function
$R_{emp}[f]$	Empirical risk minimisation function
$K(x, x')$	Kernel functions
$(x)_+$	The positive part of x
O	Column vector of zeros
L	Loss function
α	Weight decay coefficient in MLP
α, α^*	Lagrange multipliers
σ	Variance
$\phi(\cdot)$	Basis function
$\upsilon(t)$	Rectangular window of unit amplitude
$\phi 0$	Extra basis function with activation fixed to 1
η_{sim}	Simulation accuracy
*	Convolution
$a(t)$	Revised window model time domain average
$A(t)$	Fourier transform of $a(t)$
C	SVM tolerance parameter
$c(t)$	Impulse signal
$C(t)$	Fourier transform of impulse signal
D	Training data set

E	Cost function
$e(t)$	Noise signal
e_{sim}	Response error
f	Frequency
f_f	Frequency of trigger signal
f_{inner}	Inner activation function
$f_{\max}$	Maximum frequency
f_{outer}	Outer activation function
f_s	Sampling frequency
$g(t)$	Deterministic periodic function of period T
$h(x^n)$	Interpolation functions
k	Number of gear rotations
M	Number of hidden units
N	Number of impulses in impulse train
n	Index for training pattern in MLP
n_t	Residual signal that is time locked to period T
$r(t)$	Infinite train of impulses
$R(t)$	Fourier transform of infinite train of impulses
t	Time
T	Period
t_k	Training target
$\mathbf{t}^{\mathrm{n}}$	Target consisting of N input vectors
T_R	Period of rectangular window
T_s	Period between the sample points
T_t	Period of impulse signal
$V(f)$	Fourier transform of rectangular window
$\mathbf{W}$	Matrix of weights (w_{n})
$w_{j0}^{(1)}$	Bias for hidden unit j
$w_{ji}^{(1)}$	First layer weights
w_{k0}	Radial basis function biases
w_{kj}	Weight parameters
w_{kj}	Basis function weights

X	Input to neural network
$\mathbf{X}$	Input space
$x(t)$	Time signal
$X(t)$	Fourier transform of time signal
X_k	Training input
$X_{\max}$	Maximum value of vibration during a given interval
x_n	Repetitive component of noise signal
$\mathbf{x}^{\mathrm{n}}$	Data set consisting of N input vectors
x_p	Periodic component of signal
x_r	Continuous random process
Y	Output of neural network
$y(t)$	Time domain average
$y_{achieved}$	Obtained output
$y_{desired}$	Desired output
y_k	Output of MLP network
$z(t)$	Numerically generated time signal

Abbreviations

CG	Conjugate gradient
DSP	Digital signal processing
KKT	Karush-Kuhn-Tucker condition
MLP	Multi-layer peceptron
RBF	Radial basis function
RMS	Root mean square
RMSE	Root mean square error
SB	Side band frequency
SCG	Scaled conjugate gradient
SVMs	Support vector machines
TDA	Time domain average