Significance of Incorporating Chebfun Coefficients in Improved Machine Condition Monitoring System

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Objective

- To propose a feature dependent-machine condition monitoring system, by using chebfun coefficients and regularized least square classifier, for machine fault diagnosis.

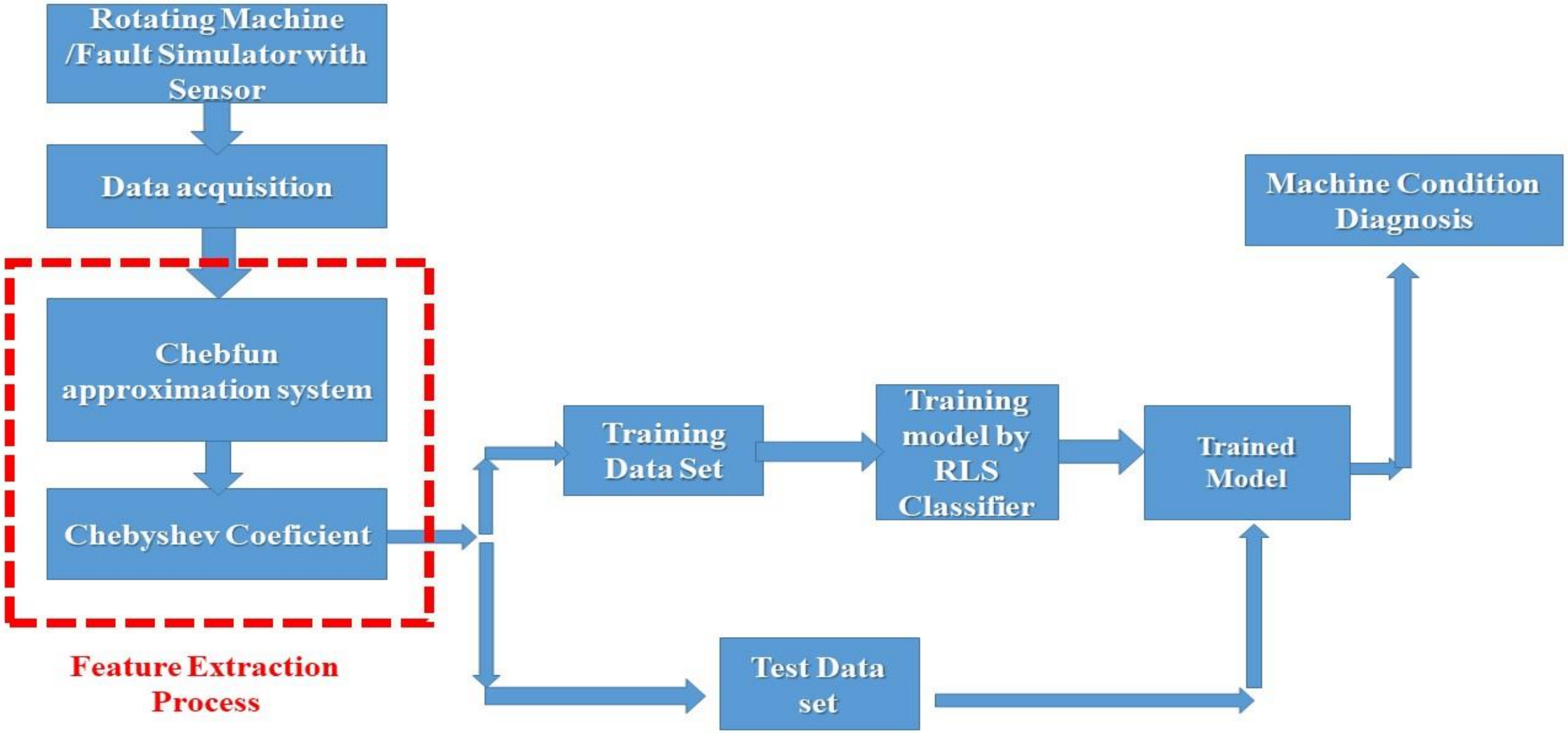
Introduction

- For any rotating mechanical system bearing and gears are one of important parts. If any of this parts fails, it can result to catastrophic failure and cause huge loss to the company. Thus requires a condition monitoring system in place.
- **A Machine Condition Monitoring System -** helps in continuously monitor the heath of the system by collecting, processing and interpreting the data. Through this system real-time operating machines can be monitored and predict the failures well before.
- **How does it work?** – Vibrational analysis : All machines irrespective of their conditions have certain frequency of vibration whether the machines are running in good or fault conditions.
- So we propose a system by using vibrational analysis and putting machine learning algorithm for pattern classification.

Existing Methods

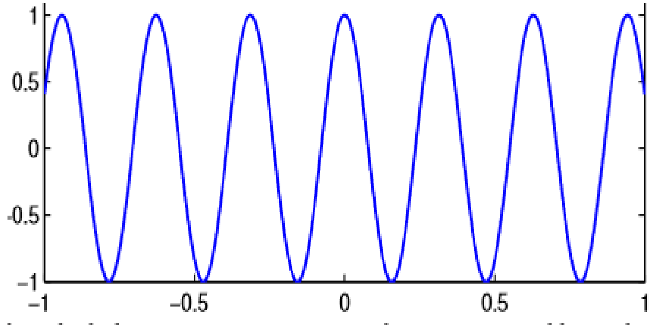
Features	Classifier	Fault Category	No-of Class
Statistical Features	Regularized Least Square	Bearing	12
Cyclo-Stationary Features	Decision Tree	Bearing	4
Cyclo-Stationary Features	Non- Probabilistic SMO	Bearing	4
Cyclo-Stationary Features	Probabilistic SMO	Bearing	4
Cyclo-Stationary Features	Regularized Least Square	Bearing	4
Statistical Features	c-SVC	Bearing	12
Statistical Features	nu-SVC	Bearing	12
Statistical Features	PSVM	Bearing	4
Statistical Features	J48	Gear	7
Statistical Features	NN	Ball Bearing	3

Proposed System (Flow Chart)

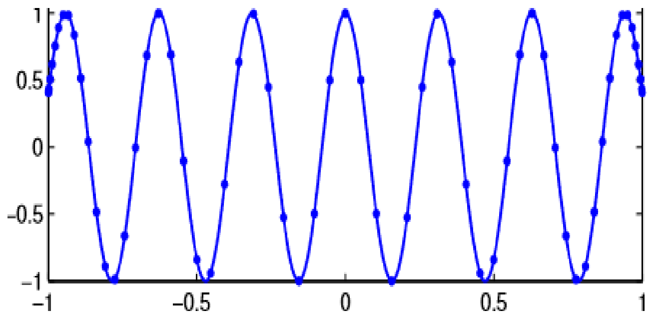


Chebfun System (Feature Extraction)

- Chebfun system is tool used for numerical computation, written in matlab code.
- In this, when the signal passed, it represents the signal in continuous function.
- Continuous function is represented by chebyshev points and represents the whole signal without loosing the contents.
- By this system, we can extract the features, which best suits in representing the signal and help in truncating the signal, which in turn reduces the computation.



Vibration Signal



Chebyshev Points

Datasets Descriptions

- **Bearing Dataset (Dataset-1)**
  - Class A : Good Condition.
  - Class B : Inner race fault condition
  - Class C : Outer race fault condition
  - Class D : Inner and Outer race fault condition
  - No of signals – 400 (100 each)
  - Sampling length : 8192

- **Gear Dataset (Dataset-2)**
  - Class A : 10% fault
  - Class B : 20% fault
  - Class C : 30% fault
  - Class D : 40% fault
  - Class E : 80% fault
  - Class F : 100% fault
  - Class G : expt no load
  - No of signals – 420 (60 each)
  - Sampling length - 2047

Results : (Classification accuracy for dataset-1)

Data Split	Kernel\ Coefficient	Accuracy (%) 10	20	30	40	50
20:80	Linear	97.5	98.54	98.03	**98.75**	95
	RBF_HO	97.5	98.12	95	97.5	98.33
	RBF_LOO	96.25	98.36	**98.75**	96.25	96
30:70	Linear	96.66	97.5	97.67	96.67	97.5
	RBF_HO	96.66	95.8	98.3	**98.33**	96.67
	RBF_LOO	96.66	97.5	**98.33**	96.67	97.5
40:60	Linear	96.87	97.5	95.62	96.25	97.5
	RBF_HO	96.87	96.87	96.85	96.25	**98.12**
	RBF_LOO	97.5	**98.12**	97.5	95	96.87

Results : (Classification accuracy for dataset-2)

Data Split	Kernel\ Coefficient	Accuracy (%) 10	20	30	40	50
20:80	Linear	91.66	96.42	**98.80**	97.61	95.23
	RBF_HO	91.66	92.85	90.47	97.61	91.6
	RBF_LOO	92.85	96.42	90.47	91.66	95.23
30:70	Linear	95.23	**96.03**	92.85	92.85	94.44
	RBF_HO	84.12	85.71	86.50	92.06	92.06
	RBF_LOO	88.50	84.12	92.06	87.30	86.50
40:60	Linear	89.88	91.66	82.73	**94.04**	89.88
	RBF_HO	77.97	86.90	78.57	82.73	81.54
	RBF_LOO	82.73	80.95	85.71	83.92	82.73

Comparison of proposed system with existing approaches:

Features	Classifier	Kernel	Fault Category	No-of Class	Accuracy(%)
Statistical Features	Regularized Least Square	Radial Basis function(RBF)	Bearing	12	96.67
Cyclo-Stationary Features	Decision Tree		Bearing	4	94
Cyclo-Stationary Features	Non- Probabilistic SMO	Linear Polykernel	Bearing	4	97.25
Cyclo-Stationary Features	Probabilistic SMO	Linear Polykernel	Bearing	4	96.75
Cyclo-Stationary Features	Regularized Least Square	Radial Basis function(RBF)	Bearing	4	96.45
Statistical Features	c-SVC	Linear Kernel	Bearing	12	98.03
Statistical Features	nu-SVC	Linear Kernel	Bearing	12	95.58
Statistical Features	PSVM		Bearing	4	95
Statistical Features	J48		Gear	7	85.1
Statistical Features	NN		Ball Bearing	3	95
Chebshey Coefficients	**Regularized Least Square**	**Linear Kernel**	**Bearing**	**4**	**98.75**
Chebshey Coefficients	**Regularized Least Square**	**Linear Kernel**	**Gear**	**7**	**98.80**

Conclusion:

- The significance of chebfun coefficients of vibration signals for machine condition monitoring is investigated.
- The proposed system has achieved an accuracy of 98% for both bearing and gear fault classification.
- The performance is compared with several other existing approaches and the results are found to be satisfactory.
- It is concluded that the proposed machine fault diagnosis system using chebfun coefficients can be used as an effective tool for real-time machine condition monitoring.

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Thank You