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VIBRATION SIGNATURE AND TIME DOMAIN ANALYSIS OF ACQUIRED VIBRATION SIGNALS FOR FAULT DIAGNOSIS OF MACHINES

SANJAY ASATI, DR. P. M. BAPAT

1. *Research Scholar & Faculty, M Patel Institute of Engg & Tech, GONDIA.*
2. *Ph D Supervisor*

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Abstract: *The operational efficiency and effectiveness of any manufacturing unit is driven by the health of machine being maintained. Well maintained machine serve better and longer and for this machine monitoring is necessary to address failures before its occurrence. Condition monitoring is an approach to detect fault likely to occur based on condition of machine. One of the methods of condition monitoring is vibration analysis where in vibration sensors are used to acquire the distinct vibration signal for particular fault condition to identify and recognition by vibration signature analysis. Among the number of faults occurring in a machine specific fault finding is difficult and need special tools and techniques. Vibration signature analysis and Time domain analysis are the techniques which determine the pattern of vibration signals and assist in assigning a particular spectrum or signature for particular unique fault condition. It is based on the fact that each fault condition generates a typical vibration signature. In the paper to determine the faulty condition in lathe machine an attempt made to carry out vibration signal analysis in time domain and further tested with statistical analysis to identify, detect and recognize fault condition. Data acquisition took place on dedicated data acquisition system developed for the purpose. The objective is to set the parameters for machine to classify the condition of machine as fault or no-fault to be further used as input for developing intelligent system based on neural networks.*

Keywords: *Fault detection, Condition Monitoring, Lathe Faults, vibration signature analysis, Time Domain Analysis, Statistical Analysis.*

Corresponding Author: MR. SANJAY ASATI

Co Author: DR. P. M. BAPAT

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INTRODUCTION

The recent time industries are facing a tough competition among competitors forcing to enhance scale of production to take advantage of production volume. Apart from this uninterrupted production run is key to any industry as delay or halt in production process or break down due to poorly performing machine/equipment not only reduces production rate but also result in increased defectives delayed delivery schedules and many other losses accumulating thereof. This encourages industry to search methods and procedure that can keep machine/equipments always in good condition and available for use on requirement. This can happen when prior to breakdown, machine may indicate some symptoms or signals alerting the user to reset machine or identify the source of unfamiliar signals emerging out. Out of the number of ways to predict the probable

In modern time industries, equipment and machinery are important part of the total productive effort making plant maintenance a vital service function wherein condition monitoring gaining wide recognition. Condition monitoring [1,2] is aided with many measuring instruments assisting identification and diagnosis of faults prior to its occurrence. Many tools & techniques are available leading to diagnosis of machine performance and machine faults. In the recent past number of instruments developed which sense health of machine and monitor performance. Machine unable to perform as per pre-specified criteria and standards are termed as underperforming and may be a result of variation in any of the operational parameters resulting in defective parts. Such conditions are faulty one and need to be addressed with reasons and sources. Sometimes machine produces unfamiliar and unwanted sound or vibrate with greater amplitude. These unwanted variations are results of deviation from the ideal condition for machine performance. Among various means to diagnose faults in machines, vibration signal based machine fault diagnosis system gained wider popularity over the years.[3-9]

2. Lathe machine faults and identification: In this paper, lathe machine is under consideration for different known fault conditions. Lathe, a very common machine being used for variety of machining operation across the industries. The performance of machine is based on its cutting and operational parameters. It observed that for given constant cutting speed and feed rate, beyond a certain depth of cut machine starts vibrating significantly resulting in poor surface finish and dimensional inaccuracies.

Such is the case common for different combination of cutting parameters. Further cutting tool condition, tool material and tool geometry also affects machine performance. As the tool starts wearing out the vibration characteristics changes and reaches to maximum extent for the completely worn out tool. Thus in between the grounded and worn out tool condition a vibration characteristic may be obtained to define and identify the good and bad tool condition responsible for normal or abnormal machining condition.[10]

Driving mechanism, spindle and spindle mountings, slide and slide-ways, tool holding device, lubrication, coolants etc. also contribute majorly to the performance of the machine. All machines vibrate under normal operating condition which has no implication on the performance but variation in any of the parameter causes the machine to vibrate beyond the normal range leading the machine to fall under faulty condition, forcing for early break down, reduced life, more defectives etc.[11]

3.Vibration analysis: Time domain methods involve indices sensitive to impulsive oscillations, like peak level, rms value, crest factor, kurtosis, averaging, & others [12]. Vibration depended fault detection procedures in machines are widely applied successfully to a a wide range of machine element and operating parameters with due emphasis on qualitative analysis of vibration signatures in the time domain.[13-15]. The damage is detected qualitatively on nature of fault by examining acceleration signatures, variation of peaks in spectra at frequencies etc. The damage detection approach utilises statistical ways to evaluate the existence and intensity of damage on a statistical basis, [15-19].The vibration signature interpretation a non-model-based pattern recognition, identify the damage based on changes in recorded vibration signatures. The quantitative features are further broken down by associating them with time-domain methods.

4.Methodology: The experimental study evaluate different fault conditions using accelerometers mounted at prominent position in proximity to the source and connected with interfacing device to computer. The accelerometer measured the axial and radial accelerations from the source as per the conditions demanded. The data processed using MATLAB software. Time domain analysis carried out to obtain vibration signature in terms of aplitude and frequency by acquiring spectra for identified fault conditions. Further, statistical analysis carried out with the data from time domain for fault detection and recognition. A series of statistical parameter as rms value, standard deviation, variance, kurtosis, skewness, crest factor obtained tabulated and plotted for evaluation.

5.Data Acquisition System: The developed MEM type accelerometer plugged in the sound port of PC backed with MATLAB software to acquire the sound wave file [20]. The data acquired normalized and conditioned to suitably meet requirements. Data acquired for time domain analysis and the characteristics of vibration signals plotted against time. The associated numeric values also obtained and an analysis carried out to ascertain known normal and faulty condition being well validated. Numerous sets of data collected for different defined normal and fault condition further tested on statistical parameters to validate the result obtained using time domain analysis. The results obtained from time domain analysis are well supportive to the objective pre-defined but measuring the characteristics only on one amplitude parameter may not always be true and need to be tested on other front. Vibrations signals are characterized for amplitude and frequency. Vibration signal can be well manipulate to get pattern using time and frequency domain analysis. The statistical approach to both time and frequency analysis make them more predominant.

6. Time Domain analysis Time domain analysis usually involve indices sensitive to impulsive oscillations, viz..peak value, rms value, crest factor analysis, kurtosis analysis, skewness testing and many more [12]. The time-domain analysis is less sensitive to suppressions of the periodicity compared to frequency domain but at initial analysis is useful to steer the direction for further analysis[21]. The time waveform of normal processed vibration signal, randomly chosen out of the acquired normal signals and abnormal signals from the same place are shown in figs 7.1. Likewise the waveform for different fault conditions is shown. (Fig7.1–fig7.5)

The time domain analysis of the signals indicates the initiation of fault in terms of occurrence to observe increased amplitude of vibrations continue to get denser. The pair of normal & abnormal waveforms exhibits the abnormal behavior of the vibrations with large magnitude after certain interval. It is evident that the waveform analysis of signals for time domain presents the faults but cannot develop sufficient confidence to arrive at definite conclusion. Still this vibration analysis can identify vibrations that are asynchronous. A detailed study of time domain waveform offers a number of simple metrics based extensive application in mechanical fault detection. The root mean square value (RMS) , crest factor(CF), Std Deviation(SD) variance(Var) kurtosis(Kur), skewness (SkF) are often used to quantify the time signal. The RMS value of the signal is the normalized second statistical moment of the signal (standard deviation). Standard deviation indicate variation or dispersion exist from the mean value. Variance measures how far a set of numbers spread out from the mean. The crest factor is defined as the ratio of the peak value to the RMS of the signal. Kurtosis is the normalized fourth statistical moment of the signal and indicates the flatness or the spikiness of the signal.[22-23]

7 Data Collection: Data collected by the developed data acquisition system [SKA] and stored as wave files for the following defined fault condition as..

Case I: The fault emerges due to excessive depth of cut

Case II: Higher feed rate results in chatter and other dimensional inaccuracies

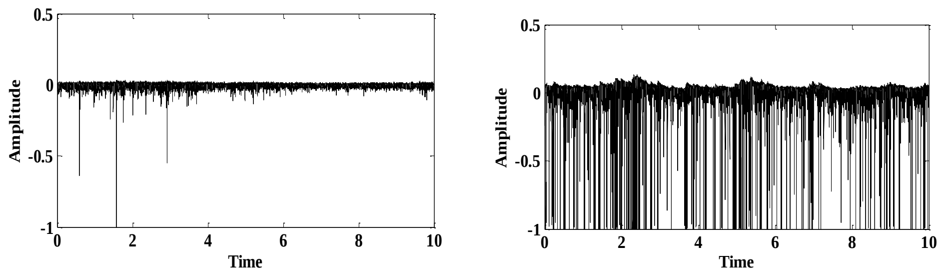
Case III: Higher operating cutting speed generates more vibration.

Case IV: Worn out tool results in enhanced chatter.

Case V: Damaged bearing introduces shocks

The faulty conditions were introduced in the machine and data acquisition done for various fault condition by setting various cutting conditions.

Case I: The cutting speed and feed rate kept constant and the depth of cut varied (0.2mm to 3mm) over a period of time to acquire vibration signal.



Normal Data **Faulty Data**

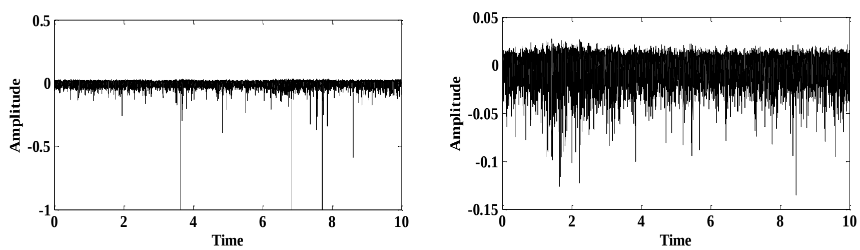
Fig 7.2; Time domain spectrum for variation in depth of cut for constant feed rate and cutting speed

Table 1 : Time Domain Data ,Depth of cut(mm)

Data Type	Depth of Cut	Statistical Parameters					
		RMS	Kur	SD	Var	SkF	CF
Normal	0.2	0.291	11.64	0.277	0.077	-3.087	1.22
	0.4	0.014	46.04	0.013	2E-04	-2.766	2.248
	0.6	0.0158	8.448	0.287	0.082	-1.865	2.002
Abnormal Data	0.8	0.016	482.8	0.016	2E-04	-10.9	2.145
	1	0.25	13.51	0.243	0.059	-3.187	1.494
	1.2	0.075	110.4	0.075	0.006	-8.73	2.978
	1.5	0.223	12.05	0.221	0.049	-1.254	3.118
	2	0.016	148.5	0.016	2E-04	-5.845	1.976

2.5	0.108	60.51	0.108	0.012	-7.061	1.217
3	0.015	413.9	0.014	2E-04	-8.446	2.01

Case II: The cutting speed and depth of cut kept constant and feed rate varied (0.05 mm/rev to 0.4 mm/rev) over a period of time to acquire vibration signal. Increase in feed rate enhance the metal removal rate but resulted in loss of finish and making operation noisy and lost accuracy of specifications.



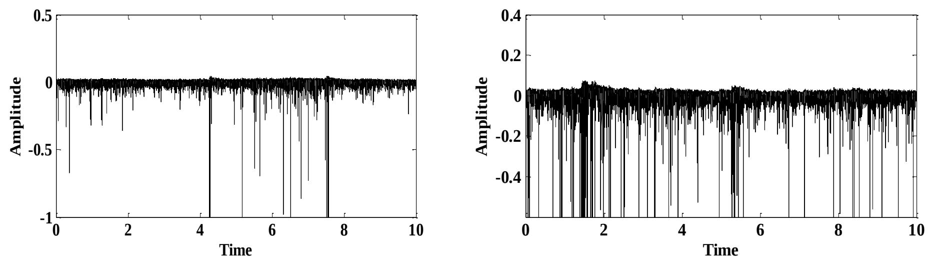
Normal Data Faulty Data

Fig 7.2; Time domain spectrum for variation in feed rate for constant depth of cut and feed rate

Table 2 : Time Domain Data ,Feed Rate (mm/rev)

Data Type	Feed Rate	Statistical Parameters					
		RMS	Kur	SD	Var	SkF	CF
Normal	0.05	0.0227	489.2	0.0224	0.0005	-13.18	1.6009
	0.75	0.0208	87.309	0.0205	0.0004	-4.578	1.6575
	0.1	0.0178	13.809	0.0145	0.0002	-1.952	1.9264
Abnormal Data	0.13	0.0124	8.1564	0.0119	0.0001	-1.443	2.1894
	1.5	0.0215	327.2	0.0213	0.0005	-9.677	1.5366
	0.18	0.0182	169.16	0.0179	0.0003	-5.147	1.646
	0.2	0.0178	48.432	0.0175	0.0003	-3.422	1.6883
	0.25	0.0191	197.69	0.0188	0.0004	-6.172	1.7115
	0.3	0.0169	219.11	0.0166	0.0003	-6.018	1.7971
	0.4	0.0142	16.075	0.0138	0.0002	-2.003	2.2149

Case III: The feed rate and depth of cut kept constant and cutting speed (15 to 50 m/min) varied over a period of time to acquire vibration signal. Rising speed generated more vibration making machine unstable



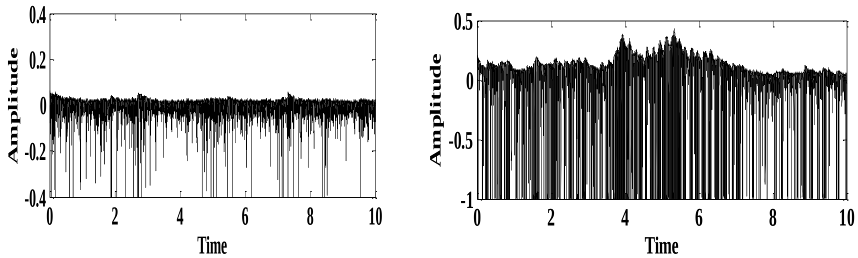
Normal Data **Faulty Data**

Fig 7.3; Time domain spectrum for variation in cutting speed for constant depth of cut and feed rate

Table 3 : Time Domain Data , Cutting Speed (M/min)

Data Type	Cutting Speed	Statistical Parameters					
		RMS	Kur	SD	Var	SkF	CF
Normal	15	0.0098	6.0471	0.0093	0.0001	-1.1195	2.2186
	20	0.0199	696.97	0.0196	0.0004	-16.111	1.8562
	23	0.0203	324.97	0.0387	0.0015	-14.642	1.6421
Abnormal	26	0.0295	446.58	0.0294	0.0009	-15.459	1.5408
	30	0.0148	877.37	0.0144	0.0002	-14.671	1.9775
	33	0.0157	15.792	0.0154	0.0002	-2.1789	1.8454
	36	0.0085	4.6379	0.0079	0.0001	-0.8616	2.1572
	40	0.0521	204.42	0.0521	0.0027	-12.083	1.4287
	45	0.0513	221.27	0.0513	0.0026	-12.755	1.3612
	50	0.0351	368.65	0.0351	0.0012	-14.983	1.5804

Case IV: For constant known cutting parameters vibration signals acquired to monitor the variation in vibration signals with wearing cutting tool. The cutting tool grounded to geometry ideal for machining It is observed that w.r.t. to tool wear vibration signals become more intensified affecting surface finish and dimensional inaccuracy



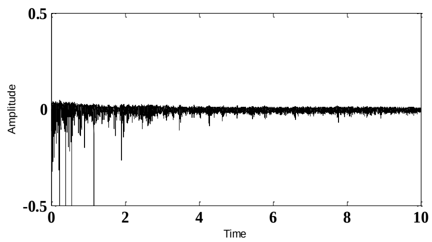
Normal Data **Faulty Data**

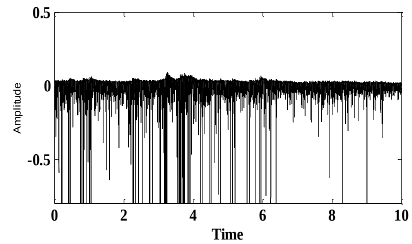
Fig 7.4; Frequency spectrum for varying tool condition for constant cutting parameters

Table 4 : Time Domain Data , Cutting Tool Wear

Data Type	Stage	Statistical Parameters					
		RMS	Kur	SD	Var	SkF	CF
Normal	1	0.5491	4.5325	0.4872	0.2373	-1.5842	1.6198
	2	0.2724	12.992	0.2591	0.0672	-3.1915	1.5958
	3	0.4002	7.0031	0.3683	0.1356	-2.1366	1.7115
Abnormal	4	0.0872	87.361	0.0871	0.0076	-8.3437	1.4589
	5	0.0408	281.1	0.0407	0.0017	-13.251	1.542
	6	0.4832	5.5492	0.4357	0.1899	-1.9403	1.4341
	7	0.1229	49.594	0.122	0.0149	-6.4023	1.4707
	8	0.2376	15.145	0.2293	0.0526	-3.311	1.8073
	9	0.3881	7.7421	0.3564	0.127	-2.3894	1.5029
	10	0.1113	56.043	0.1108	0.0123	-6.5407	2.3449

Case V: Bearing failure occurs due to failure of races, cages or balls. In this case, only ball failure is considered by introducing intentional fault during the course of data collection. This is done by damaging the balls by tempering at intervals. The vibration signals acquired keeping other parameters to stay normal and stable. The initial vibration signal acquired represents ideal condition where vibration has low amplitude and low frequency. On introduction of fault rise in amplitude and frequency observed which beyond a certain limit became excessive to describe as abnormal/fault condition characterised by higher peaks of amplitude to result poor surface finish and noise.





Normal Data **Faulty Data**

Fig 7.5; Frequency spectrum for varying tool condition for bearing failure

Table5 : Time Domain Data ,Bearing Failure

Data Type	Stage	Statistical Parameters					
		RMS	Kur	SD	Var	SkF	CF
Normal	1	0.0928	77.684	0.0927	0.0086	-7.9395	1.0665
	2	0.0957	73.697	0.0956	0.0091	-7.7738	1.0228
	3	0.091	79.043	0.0909	0.0083	-7.9649	0.9098
Abnormal	4	0.096	72.764	0.0958	0.0092	-7.6865	1.0404
	5	0.104	62.759	0.1038	0.0108	-7.1645	1.063
	6	0.1073	60.145	0.107	0.0114	-7.0427	0.9231
	7	0.0974	71.359	0.0972	0.0095	-7.6377	1.1298
	8	0.0929	75.784	0.0928	0.0086	-7.7907	1.1542
	9	0.0939	75.293	0.0938	0.0088	-7.8169	1.0433
	10	0.0915	77.642	0.0915	0.0084	-7.9026	0.9516

Discussion & Conclusion: The statistical values from tables and the plots of normal and abnormal fault condition reflect the behavior of machine being influenced by increased vibration. It provides clear indication for drawing a line between the normal and faulty state for the given fault type. The vibration signals acquired from different fault occurring locations on lathe to develope vibration acquisition system to process and obtain more information for faults. The time waveforms of the signals analyzed to obtain initial conclusions followed by statistical analysis using MATLAB of extract features of time domain. The statistical behavior of various fault conditions is studied and various conclusions are drawn for the intensity of vibration for normal and abnormal condition to classify. The conclusion is at very primary stage as it does not provide other useful information for vibration analysis as frequency and can be extracted by frequency analysis and hence acquired data needs to be tested with frequency domain and time frequency domain analysis to support the results.

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