Slovak University of Technology in Bratislava
Faculty of Informatics and Information Technologies

FIIT-xxxx-xxxxxx

Bc. Miroslav Hájek

Machinery vibrodiagnostics with the industrial internet of things

Master's Thesis

Thesis Supervisor: Ing. Marcel Baláž, PhD.

May 2023

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Master's Thesis

Study programme:	Intelligent Software Systems
Study field:	Informatics
Training workplace:	Institute of Computer Engineering and Applied Informatics
Thesis supervisor:	Ing. Marcel Baláž, PhD.
Departmental advisor:	Ing. Jakub Findura
Consultant:	Ing. Lukáš Doubravský

May 2023

SLOVENSKÁ TECHNICKÁ
UNIVERZITA V BRATISLAVE
FAKULTA INFORMATIKY
A INFORMAČNÝCH TECHNOLÓGIÍ

Návrh zadania diplomovej práce

Finálna verzia do diplomovej práce [1]

Študent:

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Študijný program:	Inteligentné softvérové systémy
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Výskumník:

Meno, priezvisko, tituly:	Marcel Baláž, Ing. PhD.

Projekt:

Názov:	Vibrodiagnostika strojov s priemyselným internetom vecí
Názov v angličtine:	Machinery vibrodiagnostics with the industrial internet of things
Miesto vypracovania:	Ústav počítačového inžinierstva a aplikovanej informatiky, FIIT STU, Bratislava
Oblasť problematiky:	Internet vecí, Spracovanie signálov, Feature engineering

Text návrhu zadania[2]

Monitorovanie prevádzkového stavu rotačných strojov za účelom včasného odhalenia poškodení je dôležité pre plynulý priebeh priemyselných procesov bez náhleho zlyhania kľúčového technického vybavenia. Nadmerné vibrácie alebo graduálna či náhla zmena ich charakteru sú spoľahlivými indikátormi opotrebenia dielcov. V mnohých prípadoch bývajú zavedené iba pravidelné pôchodzkové merania s následným vyhodnotením časových a frekvenčných priebehov kvalifikovaným personálom. Kontinuálna diagnostika a prediktívna údržba rozširujúca sa so zariadeniami IIoT spôsobuje enormný nárast objemu zaznamenaných dát. Sledovanie výchyliek operátorom a manuálna identifikácia súčiastok vyžadujúcich údržbu v celom závode sa tak stáva prakticky nerealizovateľná.

Preskúmajte spôsoby zisťovania bežných poškodení strojov z vibračných signálov a analyzujte algoritmy na redukciu množstva posielaných dát zo senzorov vzhľadom na osobitosti aplikačnej domény. Navrhnite reprezentáciu údajov na základe typických čŕt signálu, ktorá zníži výpočtové nároky na zvyšok komunikačného reťazca. Zvolený spôsob predspracovania má zároveň umožniť diagnostiku poškodení zvoleného stroja. Implementuje vaše riešenie s ohľadom na možné nasadenie na prostriedkami limitovanú senzorovú jednotku. Následne posúďte efektívnosť, porovnajte dosiahnuté presnosti diagnostiky a verifikujte voči zaužívaným postupom.

[1] Vytlačiť obojstranne na jeden list papiera

[2] 150-200 slov (1200-1700 znakov), ktoré opisujú výskumný problém v kontexte súčasného stavu vrátane motivácie a smerov riešenia

Literatúra[3]

- NANDI, Asoke Kumar; AHMED, Hosameldin. Condition monitoring with vibration signals: compressive sampling and learning algorithms for rotating machines. Hoboken, NJ, USA: Wiley-IEEE Press, 2019. ISBN 978-1-119-54462-3.
- YU, Gang. A Concentrated Time–Frequency Analysis Tool for Bearing Fault Diagnosis. IEEE Transactions on Instrumentation and Measurement. 2020, vol. 69, no. 2, pp. 371–381. ISSN 1557-9662. DOI: 10.1109/TIM.2019.2901514. Conference Name: IEEE Transactions on Instrumentation and Measurement.

Vyššie je uvedený návrh diplomového projektu, ktorý vypracoval(a) Bc. Miroslav Hájek, konzultoval(a) a osvojil(a) si ho Ing. Marcel Baláž, PhD. a súhlasí, že bude takýto projekt viesť v prípade, že bude pridelený tomuto študentovi.

V Bratislave dňa 22.2.2023

Podpis študenta

Podpis výskumníka

Vyjadrenie garanta predmetov Diplomový projekt I, II, III

Návrh zadania schválený: áno / nie[4]

Dňa: ....

Podpis garanta predmetov

[3] 2 vedecké zdroje, každý v samostatnej rubrike a s údajmi zodpovedajúcimi bibliografickým odkazom podľa normy STN ISO 690, ktoré sa viažu k téme zadania a preukazujú výskumnú povahu problému a jeho aktuálnosť (uveďte všetky potrebné údaje na identifikáciu zdroja, pričom uprednostnite vedecké príspevky v časopisoch a medzinárodných konferenciách)

[4] Nehodiace sa prečiarknite

Declation of Honour

I hereby declare on my honour that I wrote this thesis independently under supervision of Dr. Marcel Baláž, after consultations and with use of cited literature.

Bratislava, May 2023 ....

Bc. Miroslav Hájek

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Annotation

Slovak University of Technology in Bratislava

Faculty of Informatics and Information Technologies

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Author:	Bc. Miroslav Hájek
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Anotácia

Slovenská technická univerzita v Bratislave

Fakulta informatiky a informačných technológií

Študijný program:	Inteligentné softvérové systémy
Autor:	Bc. Miroslav Hájek
Diplomová práca:	Vibrodiagnostika strojov s priemyselným internetom vecí
Vedúci diplomovej práce:	Ing. Marcel Baláž, PhD.

Máj 2022

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1 Introduction

Manufacturing is experiencing a shift in the traditional practices of asset operational status evaluation and utilization. The rise of Industry 4.0 means greater automation and robotization of the production halls to achieve optimal usage of available resources. The secondary aspect in the enterprises' endeavor, however not less important, is to keep track of the equipment wear and tear. The corrective action be it repair or replacement should be taken on time in response to the key indicators.

The goal is to preserve required safety and production efficiency when extending the useful life of machine moving parts. In the factories and logistics where this sort of equipment is vital, there is a rising interest in the ability to monitor in real-time the health of the machines and to proactively diagnose the fault to repair it without adding unnecessary costs.

Vibrations are the most nonintrusive way with which such faults can be sensed. The experts use it to distinguish faulty states and to identify the malfunction's root cause. In critical circumstances such as in the case of the large turbines in the power plants, the precautions leading to regular machinery check-ups are already in place. To reach wider acceptance and spread, the monitoring solution has to be sufficiently independent, reliable, and as self-sufficient as the model design allows it to be.

The main issue to consider in large-scale machinery monitoring using vibrations are lots of uninformative streams of samples not directly useful for the production line operator. The dashboard must aggregate these flows into trend variables with severity levels categorized based on industrial standards. The majority of signals are viewed once at the maximum therefore to store or even transmit them from the edge device in its entirety would be wasteful. The complex overview of the mechanical equipment status is attainable only when agent devices and sensors are cheap enough with a long lifespan on battery power and preferably remain physically small to reduce the additional clutter.

Attempted machine and deep learning approaches have the crucial impediment that the construction of every single machine is unique to some extent because of tolerances and variable load. The model must be trained specifically for the target environment to achieve the ideal performance. In addition, the failures are relatively rare events occurring usually in the span of multiple months. In these circumstances, it is hard to obtain a large enough sample of fault events quickly. Novelty detection is a technique that can be applied in this case.

The thesis is organized in the following manner. In the first chapter of analysis in section 1 we explore the mechanical maintenance approaches and industry standards on common fault identification. Then section 2 is all about measuring vibrations and transforming them into features meaningful in automatic fault pattern recognition. In section 3 we delve into modes of diagnosis based on reduced relevant indicators. Section 4 deals with evaluation datasets used to determine computational requirements on IIoT infrastructure. Chapter 2 defines data format and proposes processing steps to diagnose the imminent failure and different fault types. The approach taken is evaluated and validated in Chapter 6.

2 Problem analysis

In the problem analysis chapter we expore the feature extraction methods and machine learning algorithms for the fault diagnostics. The basis we build upon is the domain knowledge of the mechnical engineers about vibration signal measurement and their evaluation.

2.1 Condition monitoring

Why monitor with vibrations, Wear process curve, Fault - failure, Levels are dependant on load and lifecycle stage

2.1.1 Maintenance strategies

Reactive

Preventive

Predictive - value for the factory and assess risks asociated with potencial fault to assign them importance

[1] [2] [3] [4] [5] [6] [7]

[8] [9]

Diagnosis indicators - what we montitor? - when it fails and early signs of faulty component - RUL (Remaining useful life) models - disadvantage lot of similiar machines (homogenous) or lots of runns until failure

- Similarity

- Degradation - used by standards
- Survival

2.1.2 Vibration fault types

- frequency ranges 1 - 300 Hz (shaft), 300 - 1000 Hz, 1000 - 10000 Hz (early bearings) - Base analytical models: Jeffcott rotor - rotor dynamics, Bearnings model - Resonance frequencies of each part - machine must run at speeds not aligned with resonance frequencies - Campbell diagram - task for mechanical engineers - Faults - reasons and frequency content

- Synchrounous response - based on RPM
- Mass unbalance
- Misalignment
- Eccentricity
- Bent or bow shaft
- Cracked shaft
- Rotor rubs - friction
- Looseness
- Auxiliery mechanical systems: Gearbox, Bearings, Belt

2.1.3 Technical standards

ISO 20816 [10] Part 1

- Measurement units - displacement, velocity, acceleration
- RMS, and max. amplitude = severity
- Measurement points for sensors (axial, radial) - image, and 45 degrees
- Evaluation zones - A, B, C, D - Severity chart (Annex B) - Degradation model
- Opeartional limits - Alarm, Trips

ISO 13373 [10] [11]
[12]

- Sensor mount type in relation to sensor resonance
- Data presentation - standard display formats for analysis - trends, watefall plots ...
- Potencial causes for faults (p. 45) - use in vibration fault types

2.2 Feature engineering

Large domain knowledge with compared to other areas of machine learning (mechanics - physics)

2.2.1 Preprocessing

- Detrending - DC removal filter
- Time synchronous averaging

2.2.2 Feature extraction

[13] [14] [15] [16] [17] [18] [19] [20] [21] [22]
[23]

Statistical measures

- Standard Deviation
- Max. amplitude
- RMS amplitude
- Skewness
- Kurtosis

—

- Spectral centroid
- RMS frequency
- Root variance frequency
- Spectral kurtosis / Fast kurtogram
- Harmonics (peaks) [24] [25] [26] [27] [28] [29]
- Spectral Envelope
- Harmonic spectral deviation

—

- Energy
- Spectral negentropy [30]
- TKEO - Teager-Kaiser energy operator [31]

Signal decompositions - sparse approximations Matching pursuit algorithm optimalization problem [32]

- FFT - Short Time Fourier Transform with Hamming window and Welch averaging [33]
- CWT-SST - Synchrosqueezing Wavelet Transform (vs. Transient-extracting transform) [34] [35] [36]
- WPD - Wavelet Packet Decomposition - to approximation and detail coef. (Fejer-Korovkin wavelet) [37] [38]
- EWT - Empirical Wavelet Transform - (Meyer wavelet) [39] [40] [32] [41] [42] [43] [44]

2.2.3 Feature transformation

- Principal Component Analysis (PCA)
- Log transformation (Box-Cox Transform) to normal distribution
- Normalization (min-max, standardize)

2.2.4 Feature selection

Filter method - SelectKBest in evaluation phase

- Variance Threshold
- Pearson correlation
- ANOVA F-value
- Mutal information
- Fisher score
- Spectral feature selection algorithm (SPEC)

2.3 Diagnostics techniques

Idenification of faulty states in data streams in semi-supervised learning

[45]

2.3.1 Novelty detection

[46]

- Local Outlier Factor, Local Correlation Integral (Anomaly score) [47] [48]
- DenStream (Density based clustering - DBSCAN) [49] [50] [**aggarwal_data_2014**] [51] [52]
- Half-space Trees (Isolation forest) [53] [46]

2.3.2 Classification

- kNN + Metric Tree (M-Tree for neighbourhood queries) + Euclidian Mahalanobis distance / RBF similarity

  [54] [55] [56]

[57] [58] [59] [60]
[61]

2.4 Evaluation Datasets

(Pictures of machines)

MAFAULDA SpectraQuest's Machinery Fault Simulator (MFS) Alignment-Balance-Vibration (ABVT) 50 kHz, 5 sec. recordings, Imbalance, Horizontal/Vertical misalignment, Bearings (Overhang / Underhang) - Inner, Outer, Cage

[62]

CWRU 2 HP (1.492 kW) Reliance Electric motor Bearings - Inner, Outer 12 kHz, 48 kHz fan and drive end bearings Fault diameters of 7 mils, 14 mils, 21 mils, 28 mils, and 40 mils (1 mil=0.001 inches) in diameter were introduced separately at the inner raceway, rolling element (i.e. ball) and outer raceway. Faulted bearings were reinstalled into the test motor and vibration data was recorded for motor loads of 0 to 3 horsepower (motor speeds of 1797 to 1720 RPM).

[57] [63]

Rotating Shaft Shaft - unbalances of different sizes 4 kHz

2.5 Sensor and microcontroller

[64]

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Appendix A: Resume

Appendix B: Plan of work

B.1 Winter semester

Period	Work
1st week	Consultation with the supervisor on directions of the future work based on literature review during previous semester.
2nd week	Outline the key sections of the analysis part in the thesis.
3rd week	Match supporting literature with analysis sections. Further invesigation on the feature engineering methodology in condition monitoring.
4th week	Summarize notes from condition monitoring articles and video-recordings of tutorials and conferences.
5th week	Research transformation of vibration signal to feature space using time-frequency, harmonic and energy statistical metrics. Progress report meeting with the supervisor.
6th week	Find articles and take notes about unsupervised and semi-supervised techniques in streaming data for machinery diagnostics, in order to gather information about suitable features.
7th week	TBD (Narrow down wide variety applicable methods for signal decomposition)
8th week	TBD (Write thesis section on condition monitoring and machinery fault types)

B.2 Summer semester

Appendix C: Digital medium

Evidenčné číslo práce v informačnom systéme: FIIT-xxxx-xxxxxx

Obsah digitálnej časti práce (archív ZIP):

Názov odovzdaného archívu: