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Hidden Markov models for tool wear monitoring in turning operations

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by

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Synopsis

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The classification of the condition of a machining tool has been the focus of research for more than a decade. Research is currently aimed at online methods that can process multiple features from more than one sensor signal. The most popular technique so far has been neural networks.

A new technique, very popular in speech recognition namely, hidden Markov models has recently been proposed for studies in classification of faults in mechanical systems. Hidden Markov models have excellent ability to capture spatial as well as temporal characteristics of signals, which is harder to do with neural networks.

This study applies the techniques of hidden Markov models to turning operations from strain signals recorded on a tool holder during cutting. Two classes of tool condition, "sharp" and "worn" are appointed in the data. A hidden Markov model is trained for each class and classification is done.

From unseen data the "sharp"-model achieved a 95.5% correct classification and the "worn"-model achieved a 94.5% correct classification. This is compared to a maximum likelihood classifier that achieved a "sharp" classification of 96.8% correct and a "worn" classification of 72.7% correct.

Dimensional reduction was done on the feature space extracted from the data in order that it may be used by the hidden Markov model. This technique shows how multiple features from more than one sensor signal can be used by a hidden Markov model for robust recognition.

KEYWORDS: dimensional reduction, hidden Markov model, HMM, principal component analysis, PCA, strain signals, turning, tool wear, tool condition monitoring.

Sinopsis

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Klassifikasie van die werkstoestand van snygereedskap in die vervaardiningsindustrie is al vir meer as 'n dekade die fokus van navorsing. Huidige navorsing konsentreer op prosesse wat die seineienskappe van meervoudige sensors aanlyn kan verwerk. Kunsmatige neurale netwerke is op die oomblik die mees populêre tegniek wat hiervoor gebruik word.

Baie onlangs is 'n tegniek wat algemeen vir outomatiese spraakherkenning gebruik word genaamd, verskuilde Markov modelle, voorgestel vir klassifikasie van foute in megnaniese stelsels. Verskuilde Markov modelle se vermoë om die temporale en ruimtelike kenmerke van seine vas te vat maak hulle baie geskik vir die taak.

In hierdie studie word tegnieke van verskuilde Markov modelle toegepas op vervormingsseine vanaf 'n beitelhouer tydens 'n snyproses op 'n draaibank. Twee toestande naamlik, "skerp" en "stomp" is aangewys vanuit die data. 'n Verskuilde Markov model is opgelei vir elk van die twee toestande.

Die modelle is getoets met data wat nie vir die opleiding gebruik is nie. Die "skerp" model het 'n korrekte klassifikasie van 95.5% behaal terwyl die "stomp" model 'n korrekte klassifikasie van 94.5% behaal het. Hierdie resultate is vergelyk met die van 'n maksimum waarskynlikheid klassifiseerder. Dié tegniek het 'n korrekte klassifikasie van 96.8% behaal op "skerp" beitels en 72.7% op "stomp" beitels.

'n Tegniek van dimensionele reduksie is gebruik om die dimensionaliteit van die seineienskappe te verminder, sodat dit deur die verskuilde Markov model gebruik kon word. Hierdie tegniek toon aan hoe seineienskappe van verskillende sensors deur 'n verskuilde Markov model gebruik kan word vir 'n kragtige klassifikasietegniek.

SLEUTELWOORDE: beitelslytasie, dimensionele reduksie, draaiproses, PCA, toestandmonitering, verskuilde Markov model, vervormingsseine, HMM

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Finally in humble submission, utmost gratitude to my Saviour and Lord, Jesus Christ for the talents and abilities with which He has graced me.
James 1:17 (Afrikaans version)

> "Elke goeie gawe en elke volmaakte geskenk kom van Bo. Dit kom van die Vader wat die hemelligte geskep het, maar wat self nie soos hulle verander of verduister nie."

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Acronyms

TCM	Tool Condition Monitoring
HMM	Hidden Markov Model
AR	Auto Regressive
ARMA	Auto Regressive Moving Average
RMS	Root Mean Square
NN	Neural Network
KBES	Knowledge Based Expert System
ANNBFIS	Artificial Neural Network Based Fuzzy Inference System
ANN	Artificial Neural Network
RF	Radio Frequency
SOM	Self-Organising Map
BMU	Best Matching Unit
DWT	Digital Wavelet Transform
SSE	Sum of Squares of Error
EM	Expectation Modification
PDF	Probability Density Function
AI	Artificial Intelligence
DHMM	Discrete hidden Markov model

Mathematical symbols

A	State transition probability matrix
a_{ij}	State transition probability
B	State probability distribution matrix
b_{ik}	$i - th$ state $k - th$ symbol emission probability
π	Initial state distribution vector
λ	HMM model
O	Observation sequence vector
o_i	Observation
α	forward probability
T	Time vector
t_i	Time instant
N	Integer denoting number
P()	Probability
σ	Standard deviation
x	sample
S	Skewness (Third statistical moment)
K	Kurtosis (Fourth statistical moment)
CF	Crest factor
E	Shannon Entropy
D	Dynamism
Ψ	Energy contained in a frequency band
fl	Lower frequency band
fh	Higher frequency band
S_x	One sided power spectral density
M	Dimensionally reduced feature set
P	Transformation vector
f	Frequency
f_s	Sampling frequency