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Sequential fuzzy clustering based dynamic fuzzy neural network for fault diagnosis and prognosis

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ABSTRACT

In recent years, increasing demands for more efficient high speed milling (HSM) processes have propelled the application and development of more effective modeling methods and intelligent machining approaches. Hence, a desired reference model has to incorporate more efficient and sophisticated feature extraction and artificial intelligence (AI) techniques aiming for more repeatability and generalizability.

In our work, wavelet analysis is applied for feature extraction to provide a better insight into time–frequency changes of the process. Considering the high dimension of extracted wavelet features, dimension reduction methods, such as clustering techniques are inevitable. They are applied as an interpretation layer between the feature extraction and artificial intelligence subsystems to form a new model structure for HSM with generalizability and sequential learning capability.

We introduce a new architecture that incorporates the advantages of fuzzy clustering into well known dynamic fuzzy neural networks (DFNN) to form an online condition monitoring system which is tolerant to slight drifts in process dynamics and adaptable to variations in parameters and device. Sequential Fuzzy Clustering Dynamic based Fuzzy Neural Networks (SFCDFNN) is developed and successfully applied for monitoring of an HSM process. It is able to sequentially learn the model and adapt itself to variations and also provide an estimation or prediction on the status of the process. It facilitates for nonintrusive fault diagnosis and prognosis. Lastly, its performance on modeling of experimental data is practically illustrated and compared to its other counterparts.

1. Introduction

High speed milling (HSM) is regarded as one of the most sophisticated and complicated manufacturing operations and is applied in important fields of engineering namely in aerospace engineering. Today, HSM is widely applied to fulfill the overwhelming and increasing demands for producing vital pieces for various industrial sectors, especially in aerospace industries for jet engine blades production and many military applications.

The throughput of the machining process is a critical parameter for determining the quality of a production process. Large throughput as well as the surface quality of the product is directly related to the change in the total production rate and the overall gain. Early research in this area started in the late 1970s and early 1980s [1]. Afterwards, many methods were suggested for the production monitoring to beef up the quality of the process. Deliverables of these works were often demonstrated in the form of mathematical models or artificial intelligence based models [2,3].

Therefore, many investigations were conducted on this process aiming for modeling its nature and improvement of its products as well as extending tool life. To achieve these goals, it is necessary to develop a reference model based on experiment data utilizing available modeling techniques such as artificial intelligence (AI).

Common goal was to accomplish better surface quality and extended tool life. This knowledge engine eases the extraction of the inherent relationship between all the effective parameters, sensor signals, and process results employing the most descriptive models for the studied case and its objectives [4,5].

Knowing the complexity of the milling signals, time and frequency features of sensor signals are often used in many investigations [3,6,7]. In some studies, these features are incorporated with some other parameters from cutting conditions to make the

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Nomenclature, acronyms and mathematical symbols

AE	acoustic emission
AI	artificial intelligence
BCCD	best cutting condition determination
CWT	continuous wavelet transform
CFFNN	cascaded feed forward neural network
DFNN	dynamic fuzzy neural network
Dc	depth of cut
DWT	discrete wavelet transform
ERR	Error Reduction Ratio matrix
Fc	feed rate
FCM	fuzzy C-means
HSM	high speed milling
MRE	mean relative error
Ra	roughness profile, arithmetic average
RBF	radial basis function
RMS	root mean square
RPM	rotation per minute
Vc	rutting speed
TCM	tool condition monitoring
$Uc_k(i)$	assigned weight or cardinality to the cluster k
β	forgetting factor
$X=(x_1,\ldots,x_r)$	input data in r dimensional space
C_j	cluster center
R_j	jth rule
x_i	elements of input data
A_{ij}	membership function on ith input element of uth rule
D_{ij}	distance of input observation i from cluster center j
y	output variable
(X_i, t_i)	input/output observation at time or iteration i
e_i	estimation error
i	i-th iteration
e_{max}	predefined maximum error
e_{min}	minimum error which defines the desired accuracy
ε	convergence constant
d_{max}	largest distance acceptable between the cluster centers
d_{min}	smallest distance acceptable between the cluster centers
γ	decay constant
k_{err}	prespecified error reduction ratio threshold
η_i	importance of rule i

model comprehend the tool wear and changes in the quality of the surface while the process is running [3].

Time–frequency transformations such as continuous and discrete wavelet transform were also applied as feature extraction for milling signals [3]. It is reported that the distribution of energy patterns in wavelet scales of cutting signals are changing according to gradual change in tool condition [3,8,7,9,10]. Usually time–frequency features consist of high-dimensional vectors of data which can complicate the computations. Hence, the dimension reduction seems to be vital for simplification of the implementations. The overall tool condition monitoring (TCM) system is depicted in Fig. 1 which is similar to the fault diagnosis system proposed by [11,12].

Accuracy, consistency and repeatability of these models requires that the structure of the reference model is chosen to have more robustness toward the replacement of the tool. Early models, mostly dependent on the geometry of the tool and the workpiece as well as cutting conditions as the key parameters on the milling process, while state-of-the-art models employ many more parameters such as cutting length and/or cutting signals, tool and workpiece design and materials, to make such models precise [14,15].

Any replacement or change in the tool must always be followed by suitable modifications in the condition monitoring systems. Therefore, it will be an improvement for the existing proposed reference models if it requires least changes in such cases. Therefore, the interpretation layer between sensors and AI modes has to be robust enough so that these variations in the system hardly affect the overall repeatability and consistency of the model. Hence, in our proposed model robustness of this layer to the tool replacement will protect the model from remarkable changes in the structure.

In the present work, a clustering based interpretation layer is proposed to apply different clustering methodologies on wavelet energy features of milling signals. In this structure, two main characteristics are underlined for a more effective reference model. *First*, the features have to be normalized, ranging from zero to one employing clustering techniques. The standardized outputs are then to be used later by an AI modeling layer. It requires to show the consistency and repeatability of clustering results. *Second* characteristic is the repeatability of the results of same type milling tools. These two conditions must be verified to show that time–frequency signal features are stable and repeatable features for proper TCM models. In [16] it is shown that among the available clustering methods, fuzzy C-means clustering will result in better normalized outputs. Here we show that it is also more suitable to be modified for sequential clustering scheme and can be applied as the fuzzification layer in dynamic fuzzy neural networks.

As a result, it will be shown via simulations that our method provides comparable accuracy while providing some key advantages:

- Online learning capability which makes the model more tolerant to the possible drifts and variations due to aging.
- A simpler structure using less number of rules and FCM-based clustering in the first layer rather than radial basis functions.
- Comparable training time and accuracy.
- Providing a higher level insight to the process by applying the time–frequency analysis features.

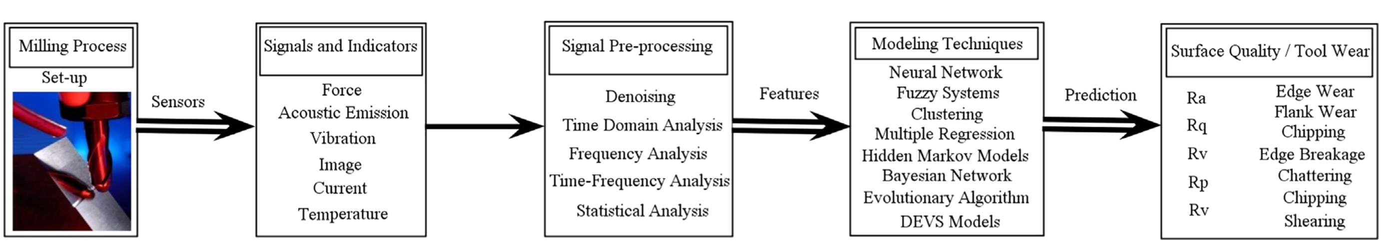

Fig. 1. Tool condition monitoring and resultant surface roughness prediction [13].