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FUZZY CLASSFICATION OF GEAR FAULT USING PRINCIPAL COMPONENT ANALYSIS-BASED FUZZY NEURAL NETWORK

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ABSTRACT

Condition assessment of machinery components such as gears is important to maintain their normal operations and thus can bring benefit to their life circle management. Data-driven approaches haven been a promising way for such gear condition monitoring and fault diagnosis. In practical situation, gears generally have a variety of fault types, some of which exhibit continuous severities of fault. Vibration data collected oftentimes are limited to reflect all possible fault types. Therefore, there is practical need to utilize the data with a few discrete fault severities in training and then infer fault severities for the general scenario. To achieve this, we develop a fuzzy neural network (FNN) model to classify the continuous severities of gear faults based on the experimental measurement. Principal component analysis (PCA) is integrated with the FNN model to capture the main features of the time-series vibration signals with dimensional reduction for the sake of computational efficiency. Systematic case studies are carried out to validate the effectiveness of proposed methodology.

1. INTRODUCTION

Gears are one of the most critical machinery components in industry. Condition monitoring and fault diagnosis have shown benefits to ensure the safe and normal operations of gears. Vibration signals have been widely used in the practice of gear fault diagnosis because they are easily measured with low-cost sensors, and contain sufficient information to reflect the health condition of gear system [1, 2]. Fault diagnosis of gear system is performed upon the signal processing of measured vibration data, which aims at extracting the underlying features in data to elucidate health conditions. To facilitate such feature extraction, a number of signal processing techniques that deal with either time- or frequency-domain information have been developed and applied, including wavelet transform [3-5], Hilbert-Huang transform [6], etc. The main challenge of these signal processing-based feature extraction methods lies in the manual selection of fault-related features. The selection of useful features retrieved from signal processing is dependent on the engineering judgement and empirical experience, which oftentimes is inefficient and tedious due to the multiple attempts required.

Along with the rapid advancement of computational power, data-driven machine learning approaches have been extensively adopted to classify/identify gear fault types [7-9]. They are capable of autonomously identifying the representative features once they are trained by learning from the data. This fundamentally avoids the manual feature selection needed in signal processing-based feature extraction methods. Among those data-driven approaches, deep learning neural networks have gained significant attentions because of their enhanced feature extraction and learning ability, as well as their capability to handle the large dimension of features, such as image and video [10, 11]. Convolutional neural network (CNN) is one of the promising deep learning neural network models. Cao et al [12] utilized convolutional neural network-based transfer learning approach to classify gear fault types based on small datasets. Kim and Choi [13] integrated signal segmentation approach into convolutional neural network model for conducting gear fault identification. In order to enhance the accuracy of gear fault classification/identification, recent research efforts have been made to build a hybrid approach by combining signal processing techniques together with the neural network models. Such a hybrid approach essentially leverages the power of both methods and thus demonstrates improved capability [14,15].

It is worth mentioning here that state-of-art data-driven classifiers for gear fault identification is feasible only when the data with the same types of gear faults are used for both training and testing processes. This is however difficult to be realized in the complex industrial setting, in which an infinite number of gear faults with continuous severities may occur. It becomes unrealistic to collect the vibration data corresponding to all possible fault types in order to establish the classifiers that can enable the reliable "deterministic" classification. Instead, one may want to use vibration data labeled with a few discrete fault severities to train a model that is expected to yield the correct fuzzy or probabilistic classification of other fault severities. A desirable classification result can be described for example as "*this data sample indicates high likelihood that a gear is under 40% damage*". In this context, we aim at developing a novel classifier to handle the abovementioned classification task with fuzzy essence. Specifically, in this research we build a fuzzy neural network (FNN) model [16] based on the experimentally measured time series signals under different gear healthy conditions, which are pre-processed via principal component analysis (PCA) [17].

The remainder of this paper is organized as follows. In Section 2, the proposed methodology is presented which includes fuzzy neural network (FNN) and principal component analysis (PCA). Section 3 demonstrates comprehensive case studies regarding how to employ above methodology to conduct the fuzzy classification of gear fault types in terms of measured time-series vibration signals, followed by the concluding remarks in Section 4.

2. METHODOLOGY FORMULATION

In this section, we first introduce the fuzzy neural network (FNN) and its general architecture and layers. We then briefly outline the principal component analysis, which will be integrated into FNN to facilitate the numerical analysis.

2.1 Fuzzy neural network (FNN)

Fuzzy neural network (FNN) is a neuro-fuzzy system that is one specific type of neural network models [16]. As compared to the general neural network models, e.g., multilayer perceptron neural network (MLP), fuzzy neural network primarily aims to learn linguistic/fuzzy rules via model training. The essence of FNN is that it must contain one fuzzification layer consisting of multiple fuzzy rules to be trained. In order to enhance its feature learning ability, the general architecture also allows the incorporation of other types of layers, such as fully connected layers which are commonly seen in a lot of neural network models. Figure 1 shows one representative architecture of FNN model. The details of layers involved are described below.

1. Input layer – this layer conveys the input information into network. Each neuron of this layer carries one feature of input sample.
2. Fuzzification layer – this layer is the key layer used to represent the way of fuzzy human reasoning. The fuzzy rules are readily integrated into this layer, and they are characterized by so called membership functions, which map the point from input space into a membership value (or degree of membership). Membership functions generally are built from several basic functions: piecewise linear functions, Gaussian distribution function, sigmoid curve, and quadratic and cubic polynomial curves [16].
3. Fuzzy reasoning/rule layer – this layer works in collaboration with previous fuzzification layer to mimic the process of human reasoning. Specifically, it activates its affiliated rule neurons to take actions accordingly in terms of antecedents from fuzzification layer. The resulted output of this layer is so called firing strength, which mathematically is in the form of multiplication of associated membership function values. The firing strength is capable of differentiating the samples in terms of samples' input features. The discrepancy of samples will become more obvious especially when more features are introduced.
4. Defuzzification layer – it fundamentally is a fully connected layer that is widely used in any type of NN model.
5. Softmax layer – it performs normalization function of the output values from defuzzification layer to yield probability values of all classes.
6. Output layer – it assigns the class in terms of probability values from softmax layer.

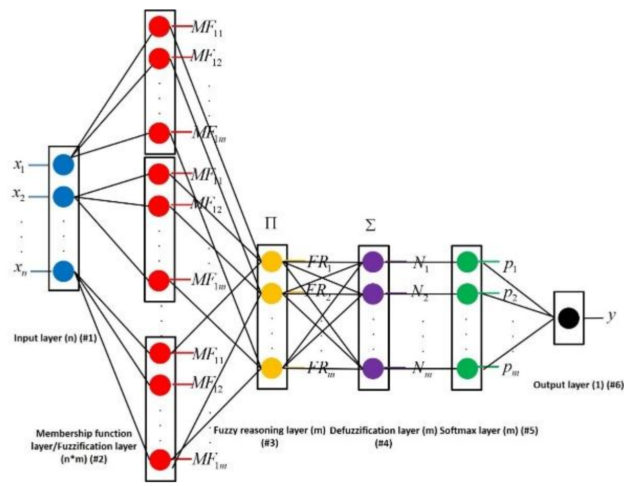

FIGURE 1: ARCHITECTURE OF FUZZY NEURAL NWTEORK (FNN) MODEL.

2.2 Principal component analysis (PCA)

Principal component analysis (PCA) is a statistical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables (entities each of which takes on various numerical values) into a set of values of linearly uncorrelated variables called principal components [17]. The principal components (PCs) are ranked in terms of feature variances among all data samples. Therefore, PCA not only results in the most differential features of samples, but also achieves the input data compression to facilitate the succeeding FNN model training. The significantly reduced input features greatly favor the computational efficiency enhancement. On the other hand, more input features (some of them may not be quite influential to output) much likely result in overfitting issue and hence degrade the performance of FNN.

3. CASE ILLUSTRATION

In this section, we carry out a case study, i.e., gear fault classification with fuzzy expression based on the experimentally measured time-series data.

3.1 Data acquisition

In this research, the experimental data are collected from a benchmark two-stage gearbox with replaceable gears a shown in Figure 2. The gear speed is controlled by a motor. The torque is supplied by a magnetic brake which can be adjusted by changing its input voltage. A 32-tooth pinion and an 80-tooth gear are installed on the first stage input shaft. The second stage consists of a 48-tooth pinion and 64-tooth gear. The input shaft speed is measured by a tachometer, and gear vibration signals are measured by an accelerometer. The signals are recorded through a dSPACE system (DS1006 processor board, dSPACE Inc.) with sampling frequency of 20 KHz.

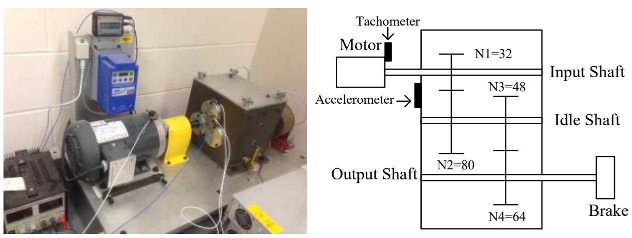

FIGURE 2: BENCHMARK GEARBOX SETUP.

There are 9 different gear conditions that are intentionally created onto pinion on the input shaft including healthy condition, missing tooth, root crack, spalling, and chipping tip with 5 different severities (Figure 3). For each gear condition, 104 signals are collected using the experimental gearbox system. For each signal, 3,600 angle-even samples are recorded in the course of 4 gear revolutions first for the case study.

FIGURE 3: 9 PINIONS WITH DIFFERENT HEALTH CONDITIONS (5 SEVERITIES FOR CHIPPING TIP).

3.2 Training and implementation

Data configuration and problem set-up

We have a total of 936 time-series samples with 9 labeled fault types. Each fault type has 104 samples, showing the data balance required for classification analysis. We formulate a fault classification problem. Here we assume we have unknown labels for 2 fault types with continuous severities. We aim at building a discriminative FNN model by training samples with other 7 fault types, and use that model to test samples with 2 unknown fault types. Details can be referred to Table 1.

Table 1. GEAR HEALTH CONDITIONS

ID	Fault Types	Fault Type Attribute
1	Healthy	Labeled/train
2	Missing tooth	Labeled/train
3	Crack	Labeled/train
4	Spalling	Labeled/train
5	Chipping_tip_5 (least severe)	Labeled/train
6	*Chipping_tip_4*	*Unknown/test*
7	Chipping_tip_3	Labeled/train
8	*Chipping_tip_2*	*Unknown/test*
9	Chipping_tip_1 (most severe)	Labeled/train

This set-up yields a total of 728 training samples and 208 testing samples. Each sample has 3,600 acceleration time series data points. In order to fit FNN model with tractable training effort, PCA is implemented on each sample for data dimensionality reduction. The 2-D projections of first 4 PCs based upon training datasets are given in Figure 4. Different colors indicate different fault types. Apparently, lower-order PCs generally have more clear boundaries of formed clusters. Care should be taken when analyzing classification accuracy. As samples with unknown fault types are not used for training and these samples essentially fall within specified continuous severities on chipping tip, the result will be considered as correct when the samples with true label chipping_tip_4 are identified as chipping_tip_5 or chipping_tip_3. Similarly, it's considered to be correct when the samples with true label chipping_tip_2 are identified as chipping_tip_3 or chipping_tip_1.

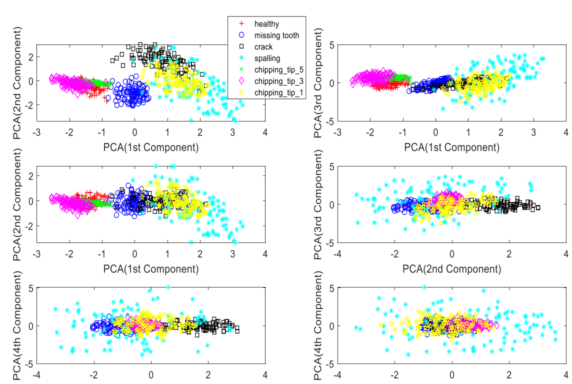

Figure 4. PRINCIPLE COMPONENTS EXTRACTED FROM TRAINING SAMPLES WITH 7 LABELED FAULT TYPES.

Establishment of fuzzy neural network (FNN) model

Following the architecture shown in Figure 1, here we specify the parameters required to finalize the establishment of FNN for training:

1. Input layer. Since in this study each time series sample is pre-processed and converted to several primary features through dimensionality reduction utilizing PCA, the number of nodes in input layer, i.e., n therefore denotes the number of principal components (PCs). Here we use 3 PCs to initiate our analysis.
2. Fuzzification layer. In this study, we choose the Gaussian membership function to describe the fuzzy sets. Each input feature will be processed by ($m \times q$) numbers of membership functions. Therefore, the number of membership functions in this layer is $(n \times m \times q)$. Here, m denotes the number of fault types (7 in this case), and q denotes the size of clusters (set as 1 in this case for sake of model simplicity). Note, the size of clusters definitely will increase the scale of model.
3. Fuzzy reasoning/rule layer. The total number of possible rules to cover all scenarios theoretically is $(m \times q)^n$ (q is selected as 1). For the sake of simplicity, here we assume that the rules are subject to self-correlation, which reduces $(m \times q)^n$ to $(m \times q)$. The details of rules are included in Table 2. Such rule set-up has some merits: 1). each rule in Table 2 solely affects the probability output of one relevant fault type, which matches our basic understanding; 2). the model stays simple by keeping a small number of nodes in this layer.
4. Defuzzification layer. The total weights in this layer to be optimized is m, which is equal to the number of outputs in fuzzy reasoning layer when $q = 1$ in this case. This can be easily paired with m probability values of relevant fault types in final output.

Table 2. FUZZY LOGIC RULES

Rule ID	Fuzzification layer #2 /antecedent	Fuzzy reasoning layer #3/consequent
1	If (x_1 is MF_{11}) AND (x_2 is MF_{21})AND …AND (x_n is MF_{n1})	$\gamma_1 = \prod_{i=1}^{n} \nu_{i,1}$
2	If (x_1 is MF_{12}) AND (x_2 is MF_{22})AND …AND (x_n is MF_{n2})	$\gamma_2 = \prod_{i=1}^{n} \nu_{i,2}$
3	If (x_1 is MF_{13}) AND (x_2 is MF_{23})AND …AND (x_n is MF_{n3})	$\gamma_3 = \prod_{i=1}^{n} \nu_{i,3}$
4	If (x_1 is MF_{14}) AND (x_2 is MF_{24})AND …AND (x_n is MF_{n4})	$\gamma_4 = \prod_{i=1}^{n} \nu_{i,4}$
5	If (x_1 is MF_{15}) AND (x_2 is MF_{25})AND …AND (x_n is MF_{n5})	$\gamma_5 = \prod_{i=1}^{n} \nu_{i,5}$
6	If (x_1 is MF_{16}) AND (x_2 is MF_{26})AND …AND (x_n is MF_{n6})	$\gamma_6 = \prod_{i=1}^{n} \nu_{i,6}$
7	If (x_1 is MF_{17}) AND (x_2 is MF_{27})AND …AND (x_n is MF_{n7})	$\gamma_7 = \prod_{i=1}^{n} \nu_{i,7}$

According to the definition of model architecture, we can train the model based on training datasets and use the well-trained model to predict the output under other testing inputs. The analysis is facilitated by MATLAB Fuzzy Logic Toolbox. Here, it's noteworthy that the architecture shown in Figure 1 is used for training. When we test the samples that essentially do not belong to those 7 fault types, we extract the outputs from fuzzy reasoning layer and directly normalize the outputs for fault type classification. In other words, we remove the defuzzification layer in current architecture in order to enable the classification result with fuzzy nature.

The testing/classification results of 104 samples for each unknown fault type, i.e., chipping_tip_4 and chipping_tip_2 are shown in Figures 5 and 6. In those two plots, the horizontal and vertical axes respectively indicate the testing sample index and the normalized probability values of 7 known fault types given the testing samples. Therefore, at each testing sample, there are 7 probability values distributed vertically. It can be observed that healthy condition and chipping_tip_5 are two dominant fault types identified for the testing samples with true fault type: chipping_tip_4 as their identified probability data points locate at the top area (approach probability value 1). On the other hand, other fault types make very little contribution. While fault type chipping_tip_3 is primarily identified for the testing samples with true fault type: chipping_tip_2, relatively uniform distribution of probability data points illustrates the engagement of other identified fault types.

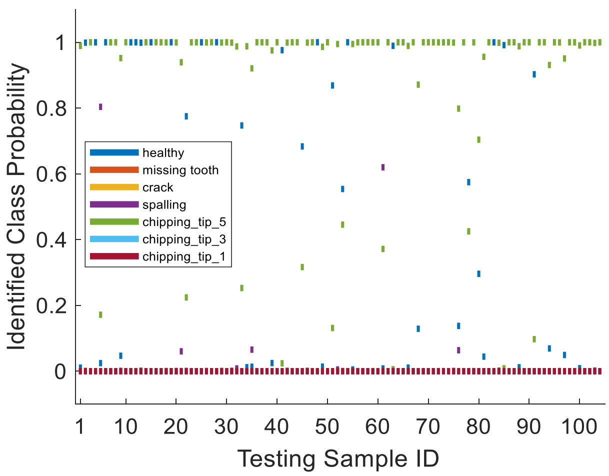

Figure 5. NORMALIZED PROBABILITIES OF FAULT TYPES OVER TESTING SAMPLES WITH TRUE FAULT TYPE: chipping_tip_4 (NUMBER OF PCS = 3).

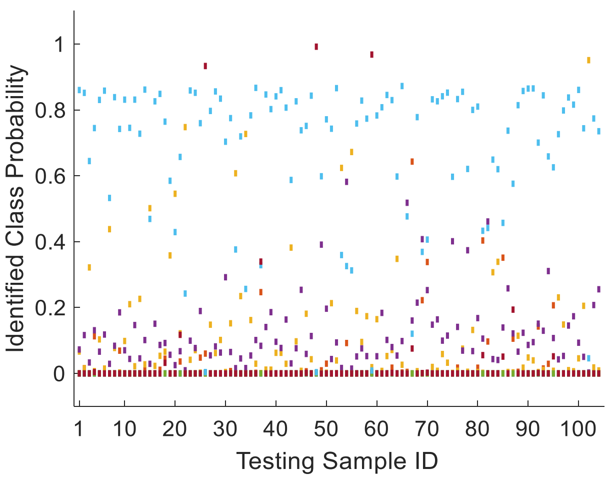

Figure 6. NORMALIZED PROBABILITIES OF FAULT TYPES OVER TESTING SAMPLES WITH TRUE FAULT TYPE: chipping_tip_2 (NUMBER OF PCS = 3). (same legend with Figure 5)

In terms of the highest probability values, the most possible fault types of all testing samples can be determined. The distributions of total numbers for identified fault types are given in Figure 7. According to the accuracy definition of fuzzy classification, the numbers of correctly identified samples for fault type chipping_tip_4 and chipping_tip_2 respectively are 79 and 91 (out of 104) from Figure 7.

The results illustrate the effectiveness of FNN for coping with the fuzzy classification analysis in this study. Moreover, one may interestingly notice that the second largest number of samples with chipping_tip_4 are identified as healthy condition. It may be reasonable since the chipping_tip_4 is a minor fault scenario whose input features may resemble that of healthy condition in many relevant testing samples. The optimized Gaussian membership functions in FNN are shown in Figure 8. It can be seen that the membership functions of higher-order PC become less differentiable. Generally, these 3 PCs are necessarily incorporated into training because their membership functions among different fault types vary, either with the change of mean or variance.

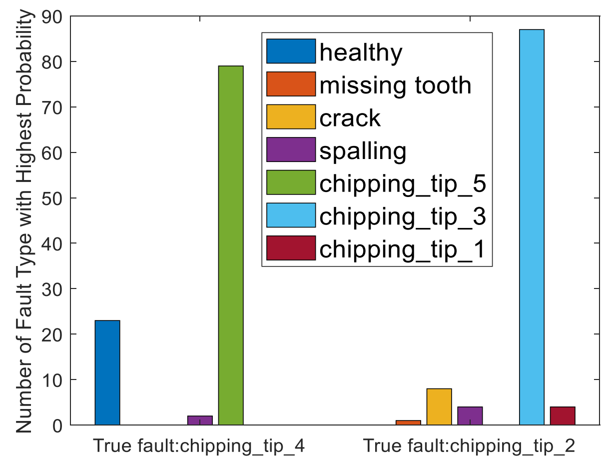

Figure 7. FUZZY CLASSIFICATION ACCURACY EXAMINATION: NUMBERS OF FAULT TYPES IDENTIFIED GIVEN TESTING VIBRATION SIGNALS (NUMBER OF PCS = 3).

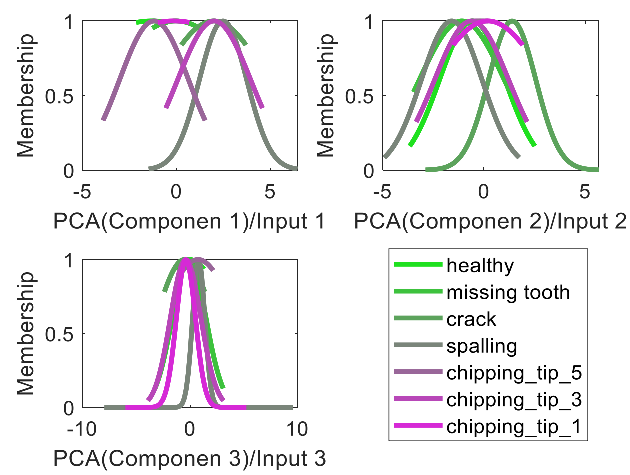

Figure 8. OPTIMIZED GAUSSIAN MEMBERSHIP FUNCTIONS (NUMBER OF PCS = 3).

It's noteworthy here that the FNN is able to magnify the probability of the most possible fault type identified following the mathematical form of firing strength. The firing strength enables the normalized probability values of the most possible fault type and others respectively to approach 1 and 0 as long as the sufficient differentiable features are involved. Therefore, except the most possible fault type, other fault types cannot be ranked due to their nearly zero probability values, which can be clearly illustrated in Figure 5. Figure 6 on the other hand can indicate the ranking of involved fault types given certain testing sample.

4. CONCLUDING REMARKS

In this research, we establish a fuzzy neural network (FNN) model that is trained upon measured vibration data labeled with limited gear fault types. We use this well-trained FNN model to fuzzily classify other possible fault types that are not included in the fault types in training data. To facilitate the training, we apply principal component analysis (PCA) onto measured gear vibration time series data to extract its features and consider these as input features of FNN model. In the case study, only first 3 principal components are selected to feed the FNN model. The results clearly verify the feasibility of this proposed methodology with good fuzzy classification accuracy.

ACKNOWLEDGMENT

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