A new damage diagnosis approach for NC machine tools based on hybrid Stationary subspace analysis

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Abstract. This paper focused on the damage diagnosis for NC machine tools and put forward a damage diagnosis method based on hybrid Stationary subspace analysis (SSA), for improving the accuracy and visibility of damage identification. First, the observed single sensor signal was reconstructed to multi-dimensional signals by the phase space reconstruction technique, as the inputs of SSA. SSA method was introduced to separate the reconstructed data into stationary components and non-stationary components without the need for independency and prior information of the origin signals. Subsequently, the selected non-stationary components were analysed for training LS-SVM (Least Squares Support Vector Machine) classifier model, in which several statistic parameters in the time and frequency domains were exacted as the sample of LS-SVM. An empirical analysis in NC milling machine tools is developed, and the result shows high accuracy of the proposed approach.

1. Introduction
Numerical control (NC) machines play important roles in industrial relying on their high automation and stability. However, NC machines generally are subject to failures by inner flimsy tools in practice, which may influence the manufacturing quality, operation safety, et al. Therefore, damage diagnosis for NC machine tools accurately and reliably has attracted considerable interests.

Tool’s damage, such as wear, gap, will occur progressively on the tool's face contacting with the chip or on the flank due to the friction between the tool and the workpiece material. A common used effective method is analysing signals gathered by sensors to reveal damage features with the help of effective signal processing techniques. Such as time-domain analysis [1], frequency-domain analysis [2], Wavelet transform [3]. However, how to choose a suitable wavelet basis function to match the machine signal structure remains an open issue despite of many alternative types currently. There is still a lack of generally accepted effective methods to solve the issue [4].

In this paper, a new damage diagnosis approach for NC machine tools were provide, which integrated Stationary subspace analysis (SSA), phase space reconstruction (PSR), and Least Squares Support Vector Machine (LS-SVM). SSA was used to separate multi-dimensional signals into the stationary components and non-stationary components without the need for independency and prior information...
of the origin signals. PSR was introduced to reconstruct dimensionality of signal to satisfy the constraint of SSA’ input data. Subsequently, the selected non-stationary components were analysed for training LS-SVM classifier model, which inputs are from eight statistic parameters in the time and frequency domains.

2. Methods

2.1. Stationary subspace analysis

Stationary Subspace Analysis (SSA) is a blind source separation algorithm which factorizes a multivariate time series into stationary and non-stationary components [5]. According to the SSA model, the observed multivariate time series \( X(t) \in R^d \) is assumed to be generated as a linear superposition of stationary components \( S^s(t) \in R^d \) and non-stationary components \( S^n(t) \in R^{d-d} \).

\[
X(t) = AS(t) = A^sA^n[S^s(t)]
\]

where A is a unknown matrix; \( A^s \) and \( A^n \) are the basis of the stationary and non-stationary subspace respectively; \( S^s(t) \) are the stationary components, \( S^n(t) \) are the non-stationary components.

The aim of SSA is to estimate the inverse mixing matrix \( \hat{A}^{-1} \) separating the stationary from non-stationary components in \( X(t) \). That is, we want to find a matrix, \( \hat{A}^{-1} = [B^s/B^n] \) with \( B^s \in R^{d \times d} \) and \( B^n \in R^{(d-d) \times d} \) that consists of the matrices \( B^s \) and \( B^n \) to the stationary and non-stationary directions respectively. Thus, if we apply such an ideal \( \hat{A}^{-1} \) to the observed data \( X(t) \),

\[
\begin{bmatrix}
\hat{S}^s_t \\
\hat{S}^n_t
\end{bmatrix} = \hat{A}^{-1}X(t) = \hat{A}^{-1}A
\begin{bmatrix}
S^s_t \\
S^n_t
\end{bmatrix} =
\begin{bmatrix}
B^sA^s & B^sA^n \\
B^nA^s & B^nA^n
\end{bmatrix}
\begin{bmatrix}
\hat{S}^s_t \\
\hat{S}^n_t
\end{bmatrix}
\]

(2)

The SSA algorithm uses the optimal stationary signal recognition criteria, only the stationary source signal \( S^s_t \) and \( n \)-space can be uniquely determined, and the non-stationary source signal \( S^n_t \) can only get its estimate \( \hat{S}^n_t \) by maximizing the non-stationary. Among them, the stationary judgment is based on the weak stationary condition, that is, a time series is stationary if its first two moments are constant over time [6]. The specific process of SSA are as follows:

1. Divide the observed data \( X(t) \) into \( N(N \geq (D - d)/2 + 2) \) continuous time epochs, and calculate the mean \( \bar{\mu}_t \) and covariance \( \bar{\Sigma}_t \) of each time period, for an arbitrary choice of \( B^s \), get the estimated mean \( \hat{\mu}_{s,t} = B^s\bar{\mu}_t \) and covariance matrix \( \bar{\Sigma}_{s,t} = B^s\bar{\Sigma}_t \) in each time period.

2. Measure the difference between the estimated stationary signal distribution and normal distribution in each time period by Kullback-Leibler (KL) divergence. Then sum up all epochs’ KL divergences, and construct the objective function \( L(B^s) \) with independent variable \( B^s \). Minimizing the objective function \( L(B^s) \), obtain the optimal stationary projection \( \hat{B}^s \), and according to the formula (2) to estimate the stationary source signal \( \hat{S}^s_t \).

\[
L(\hat{B}^s) = \min L(B^s) = \min \sum_{i=1}^{N} D_{KL} [\text{Norm}(\hat{\mu}_{s,i}, \bar{\Sigma}_{s,i})||\text{Norm}(0,1)]
\]

3. Construct the objective function \( G(B^n) \) with the above step (1) and (2). Maximizing the objective function \( G(B^n) \), obtain the optimal non-stationary projection \( \hat{B}^n \), and according to the formula (2) to estimate the non-stationary source signal \( \hat{S}^n_t \).

\[
G(\hat{B}^n) = \max G(B^n) = \max \sum_{i=1}^{N} D_{KL} [\text{Norm}(\hat{\mu}_{n,i}, \bar{\Sigma}_{n,i})||\text{Norm}(0,1)]
\]

2.2. Phase space reconstruction

Phase space reconstruction (PSR) is a Chaos technology according to the delay coordinate method proposed by Takens and Packard [7]. The idea of PSR is that the evolution of any component of a system is determined by the interaction with other components, and the time series implies the development process of each component. Considering a component, PSR take some measurement processing in fixed time delay point as a new dimension, the value of delay is considered as a new coordinate. Repeating this process at different time points, many of these points could be generated to a new space. For one-
dimensional time series $X(t)$, through different time delay $0, t, 2t, \ldots, (m-1)t$ to construct m-dimensional phase space vector.

$$X_i(t) = \{x(t + i), x(t + i + \tau), x(t + i + 2\tau), \ldots, x(t + i + (m-1)\tau)\}, i = 0, 1, \ldots, m - 1$$

where $t$ is the time delay and $\tau$ is the embedding dimension.

$$P = \begin{bmatrix}
x_1 & x_2 & \cdots & x_{N-(m-1)t} \\
x_{1+t} & x_{2+t} & \cdots & x_{N-(m-2)t} \\
\vdots & \vdots & \ddots & \vdots \\
x_{1+(m-1)t} & x_{2+(m-1)t} & \cdots & x_{N}\end{bmatrix}$$

The key of phase space reconstruction is the time delay $t$ and embedding dimension $\tau$. Values of $t$ and $\tau$ are obtained by the mutual information method and Cao’s method [8], respectively.

### 2.3. Least squares support vector machine

Support Vector Machines (SVM) is a powerful methodology for solving problems in nonlinear classification, function estimation and density estimation, which has been introduced within the context of statistical learning theory and structural risk minimization. Least squares support vector machine (LS-SVM) proposed by Suykens [9] is one of the most influential achievements in recent years.

Given a training data set $\{(x(t), y(t)), t = 1, 2, \ldots, N\}$, $x(t) \in \mathbb{R}^m$ is the input data, $y(t) \in \mathbb{R}$ is the category label corresponding to $x(t)$, and $N$ is the training samples number. In LS-SVM, the estimation model is $y_t = w^T \phi(x_t) + b + e_t$, where $\phi(.)$ is a nonlinear transformation that map $x(t)$ to the high feature space, $w$ is weight vector, $b$ is intercept, and $e_t$ is the error term that is assumed to be independent and identically distributed (i.i.d) with zero mean and finite variance.

According to [9,10], the LS-SVM model is expressed in dual form as: $\hat{y}(z) = \sum_{i=1}^{N} \alpha_i K(z, x_t) + b$. Note that, the unknown items $w$ and $\phi(.)$ are not included in the dual model, the mapping transformation operations are achieved implicitly through the use of kernel function $K(,\ldots)$. That is to say, it is necessary to find the expression of mapping function $\phi(.)$. For the kernel function $K(,\ldots)$, it is not difficult to determine the kernel function, and the function satisfying the Mercer theorem can be used as a kernel function. There are several choices presently, such as linear kernel, spline kernel, and RBF kernel.

### 2.4. Damage diagnosis approach based on hybrid Stationary subspace analysis

The damage diagnosis approach for NC machine tools in this paper includes two phases. The first phase focuses on model training, sample feature parameters in different tool states are obtained by the proposed method. Firstly reconstructed multi dimensions signal are transformed by PSR, stationary parts and non-stationary parts are extracted from multi-dimensional signals by SSA. Subsequently, some dimensionless statistic time-frequency parameters in non-stationary components are calculated as the sample data of LS-SVM for classification. The second phase is damage detection for unknown working tools. The specific procedure is constructed through the following main steps as shown in Figure 1.
3. Experiment and discussion

3.1. Experiment Design

The GSVM714A NC milling machine is used for the experimental test. The cutting tools used in this test are carbide tools #RPMW1003# in a face milling cutter #EMR 5R160-40-8T# with four teeth. The experimental setup for the in-process detection of tool fault is illustrated in Fig 2. The tool vibration signals are monitored by a laser vibrometer by Polytec Inc. (shown in Fig 3), and sent to a data acquisition instrument (ECON Avant (MI-7016)) and a portable computer.

Tool states in this experiment are alternatively three situations: normal, mild wear, and severe wear (shown in Fig 4). Aluminum alloy samples #7075-T351# of size (150 mm, 100 mm, 500 mm) are fixed on the machining center. In this experiment, cutting speed and depth are 1000 rpm and 1 mm respectively.

3.2. Result and Discussion

In this experiment, three tool damage classes were measured including (1) normal tool, (2) mild wear tool, (3) severe wear tool. It is assumed that all investigated tools have the same damage mechanism. The vibration signals were measured and the sampling frequency was 48,000 Hz. Vibration signals in three tool classes are measured 30 times and divided into two parts: 20 times as training data and 10 times testing data. The training set is used to train model in Matlab R2012.

In the first phase model training, the two parameters $t=9$ and $\tau=4$ by the mutual information method and Cao’s method. The result of PSR are chosen as input for the SSA decomposition, and extracted to 3 ($d=3$) stationary components and 1 non-stationary component. Figure 5 shows a SSA result of the class of mild wear tool three classes in sample data. Then eight dimensionless time-frequency parameters outlined in [11] were choose in the non-stationary component, which are the training sample data of LS-SVM classifier model. Gaussian RBF kernel was selected in LS-SVM.

The classification results of hybrid SSA proposed are shown in Table 1 for testing data. According to Table 1, 10 normal tool groups can be correctly identified, however, the accuracy of mild wear groups and severe wear groups are 80% and 90%, there are 2 mild tool groups were identified to severe tool class, and 1 severe tool group was identified to mild tool class. The hybrid SSA method proposed was compared with the original LS-SVM. The original LS-SVM method denotes that the original vibration signals measured in experiment are the input of LS-SVM, which do not extract signal by SSA and PSR. As shown in Table 1, the accuracy of the original LS-SVM is less than hybrid SSA. There are 1 normal group, 4 mild wear groups and 2 severe wear groups get error results, and the accuracy of normal, mild wear and severe wear groups are 90%, 60% and 80%. The hybrid SSA proposed in this paper is outperform with original LS-SVM. SSA can extract effectively stationary sources and non-stationary sources, and obtain valuable information to damage diagnosis.
Figure 2. Experiment setup

Figure 3. Measuring vibration signal by a laser vibrometer

Figure 4. Samples of milling cutter shape and different tool states
Figure 5. SSA results of mild wear tool sample

Table 1 Compare in result of different methods

| Methods              | Testing classes | Testing result | Accuracy |
|----------------------|-----------------|----------------|----------|
|                      | normal tool     | mild wear tool | severe wear tool |     |
| Hybrid SSA proposed  | normal tool     | 10             | 0        | 0      | 100%    |
|                      | mild wear tool  | 0              | 8        | 2      | 80%     |
|                      | severe wear tool| 0              | 1        | 9      | 90%     |
| Original LS-SVM      | normal tool     | 9              | 1        | 0      | 90%     |
|                      | mild wear tool  | 3              | 6        | 1      | 60%     |
|                      | severe wear tool| 0              | 2        | 8      | 80%     |

4. Conclusion

The present study proposes a damage diagnosis approach to NC machine tools based on hybrid SSA. Firstly, the original data set are transformed single dimensional data into high dimensional manifold signals by PSR. The SSA method is applied to extract the stationary parts and non-stationary parts from multi-dimensional signals without the need for independency and prior information of the source signals. Subsequently, the selected non-stationary components were analyzed for classification by LS-SVM, in which eight dimensionless parameters in the time and frequency domains were exacted as the inputs of LS-SVM. An empirical analysis in NC milling machine tools is developed, and the result shows the proposed approach is outperform with the original LS-SVM approach. Future work can be centered on improvement of the accuracy, efficiency and calculation speed of the proposed approach.

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