A Transfer Learning Based Unmanned Aerial Vehicle MEMS Inertial Sensors Fault Diagnosis Method

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Abstract. In this paper, we propose a novel transfer learning based micro-electromechanical system (MEMS) inertial sensors fault diagnosis method. First, the MEMS inertial sensors fault diagnosis method is formulated to a deep transfer learning problem in which the offline samples are deemed as source domain and the online samples are set to target domain features. Second, the bidirectional long short-term memory and Hilbert-Huang transformation-based feature transfer model is designed to decrease the discrepancy between SD and TD, that performs the transfer operation using intrinsic mode function features. Then we propose a convolutional neuro network-based transfer learning algorithm to further decrease deep features discrepancy and perform the fault classification tasks on TD. According to the experiments, the proposed FD method has achieved excellent fault classification performance and significantly improvement comparing with the state-of-the art methods.

Keywords: MEMS Inertial Sensors, Fault Diagnosis, Transfer Learning, Deep Learning, Hilbert-Huang Transformation.

1. Introduction
Micro-electromechanical Systems (MEMS) inertial sensors have been widely used in unmanned aerial vehicles (UAVs) because of the advantages in power consumption, price and weight, the reliability of inertial sensors has great impact on the safety of UAVs, the performance of MEMS inertial sensors can be easily affected by the working conditions\textsuperscript{(1)}, such as temperature, pressure, humidity, that may lead faults.

Data driven FD methods offers a strategy to recognize fault patterns from various data\textsuperscript{(2)}. Deep learning (DL) is one branch of machine learning that mines feature from large volume of historical data. Our research aims to recognize temperature-related fault patterns of MEMS
inertial sensors\cite{4}. DL offers an effective strategy to recognize these nonlinear and nonstationary patterns because of its advantages in complex abstract feature mining. Convolutional neural network (CNN) and long short-term memory (LSTM) are two famous DL. Many researchers adopted CNN in FD researches\cite{5}. LSTM is a widely used recurrent neural network for processing serial information. LSTM-based methods are adopted by researchers for addressing FD problems\cite{6}. Transfer learning (TL) is a model adjusting strategy that performs the model transfer tasks between domains with different distributions. In data driven FD fields, sufficient labeled source domain (SD) samples are easily obtained, however, in working conditions which belong to target domain (TD), system runs on normal condition in most of time, that makes obtaining working conditions samples with various fault patterns difficulty\cite{7}. This limitation reduces the performance of data driven FD models trained with SD features. To addressing this problem, various researchers adopt TL to FD researches\cite{8}\cite{9}.

In this paper, we propose a novel transfer learning-based unmanned aerial vehicle MEMS inertial sensors fault diagnosis method. The innovations of our research are as following:

We formulate the MEMS inertial sensors fault diagnosis method for deep transfer learning problem, the proposed FD method classifies the fault features using CNN based model.

We propose a bi-directional long short-term memory (BLSTM)-based transfer learning method to transfer the SD features to auxiliary dataset for deceasing the discrepancy with TD.

We have proposed a CNN-based transfer learning model to perform TD samples labeling and fault classifying tasks, this model is trained by labeled auxiliary dataset and unlabeled target domain dataset.

2. Transfer Learning and Deep Learning Based Unmanned Aerial Vehicle MEMS Inertial Sensors Fault Diagnosis Method

The proposed FD method is shown in Fig. 1. First, the labeled SD samples are generated by real inertial data of offline calibration condition and the TD samples are generated by the UAV aerial dynamic model with the inertial data on fault conditions. Fractions of TD samples are labeled by handcraft and the rest of TD samples are unlabeled. Second, a BLSTM regressor-based transfer learning model is proposed to map SD features to TD for generating the auxiliary features. Third, labeled auxiliary dataset is used to train CNN classifier for obtaining initial parameters. Fourth, the mix training process is performed using auxiliary dataset and unlabeled TD dataset, that labels the TD samples according to MMD and the optimizing goal is to minimize the MMD-based discrepancy and classification errors. Note that the proposed HHT in Fig. 1 is an improved HHT method with novel efficiency which is detailed in our previous work\cite{10}, we use this method to generate the IMF features in SD and TD for obtaining the robust representation of features.

![Fig 1. The proposed TL-based FD method.](image-url)
2.1. Aerial Dynamic Model-Based Target Domain

The fault samples in TD are generated by the proposed aerial kinetic simulator that include controller, aerial dynamic model, fault states, and working condition, the proposed aerial kinetic simulator are detailed in Fig. 2. First, the fault states are generated by removing the working condition-related trend components from SD samples. Second, the fault states are added to the measurements of inertial measurement unit (IMU) in sensors component. Then, TD datasets are acquired from the inertial measurements of control loop. We chose a common quadcopter aerial dynamic model \cite{11} to construct the UAV model.

2.2. BLSTM-Based Feature Transfer Learning

On the complex working conditions, the features of MEMS inertial faults are different with the fault features of offline calibration condition; even if these fault features are caused by same faults. To decrease the discrepancy between SD (offline fault features) and TD (working condition fault features), we train a BLSTM-based transfer learning model to map SD to auxiliary domain, that is detailed in Fig. 3. The proposed BLSTM features transfer learning model performs a regression task, the input features are SD features and the regression labels are TD features. The proposed BLSTM transfer learning model that consists two BLSMT layers and two fully connection layers, the first layer is a 64 neurons embedded BLSTM layer, the second layer is a BLSTM layer with 32 neurons, the last two layers are two fully connection layers with 16 neurons and one neuron. The BLSTM layers are used to extract the abstract features and time dependence information and the fully connection layers are used to regress deep features to time sequences. The outputs of the trained BLSTM model constitute the auxiliary dataset, the distribution discrepancy between auxiliary dataset and TD is decreased due to that the target of the regression model is TD. For obtaining the clear representation of fault features, we use IMFs of SD and TD as the input and output of the proposed BLSTM-based transfer learning model. Note that IMFs are generated by our previous BLSTM-based HHT \cite{10} method. The detailed procedure of training BLSTM model is shown in Fig. 3. Small numbers of SD samples and labeled TD samples are used as inputs and regression labels accordingly in training operation. For the trained BLSTM model, the inputs are labeled SD features and the outputs are auxiliary datasets with labels corresponding to SD labels.
2.3. CNN Based Transfer Learning

We propose a CNN-based TL model as in Fig. 4 to classify faults in TD. The network structure and layer configurations of each layer are shown in Table 1. For obtaining the satisfaction fault classification performance on TD. The initial CNN parameters are obtained by training with labeled auxiliary features; then, the unlabeled TD samples and labeled auxiliary samples are utilized to train CNN model. The MK-MMD algorithm [8] is used to evaluate the discrepancy of deep features between auxiliary and TD features. The optimizing goal of the CNN contains three parts: the classification error $L_a$ on auxiliary samples, the classification error $L_{T}$ on target samples that are the error $L_d$ between MK-MMD labels and TD prediction labels, the MMD discrepancy between auxiliary-based deep features and TD-based deep features. The optimization goal is as following:

$$L = L_a + L_T + L_d = \frac{1}{n_a} \sum_{i=1}^{n_a} J(\hat{y}^a_i, y^a_i) + \frac{1}{n_{T}} \sum_{j=1}^{n_{T}} J(\hat{y}^T_j, y^T_j) + \alpha \sum_{l=1}^{L} d^l(D^a_l, D^T_l)$$

(1)

where $\hat{y}^a_i$ indicates the prediction output using auxiliary features, $y^a_i$ indicates the real labels of auxiliary features, $\hat{y}^T_j$ indicates the prediction outputs using TD features, $y^T_j$ indicates the labels generated by MK-MMD algorithm, $D^a_l$ and $D^T_l$ indicate the deep features in $l$-th layer of CNN using auxiliary features and TD features respectively, $d^l(\bullet)$ indicates the MMK discrepancy, $J(\bullet)$ indicates the loss function which is cross entropy, $\alpha$ is the coefficient.

![Fig 4. CNN-based model TL model.](image)

### Table 1. Multi-scale CNN configuration

| Layer | Name | Details | Layer | Name | Details |
|-------|------|---------|-------|------|---------|
| 1     | Conv1 | Conv (3 x 3 x 32); stride: (1 x 1) | 7     | Pool 3 | Max pool (2 x 2 x 128); stride: (1 x 1) |
| 2     | Conv2 | Conv (3 x 3 x 32); stride: (1 x 1) | 8     | Multi | Concatenate features from layer 3 and 7 |
| 3     | Pool 1 | Max pool (2 x 2 x 32); stride: (1 x 1) | 9     | FC1   | FC 64 |
| 4     | Conv3 | Conv (3 x 3 x 64); stride: (1 x 1) | 10    | FC2   | FC 32 |
| 5     | Pool 2 | Max pool (3 x 3 x 64); stride: (1 x 1) | 11    | Output | Soft max (4) |
| 6     | Conv4 | Conv (2 x 2 x 128); stride: (1 x 1) |       |       |         |

2.4. Procedure of Proposed FD Method

After proposed CNN is trained using the auxiliary dataset and TD dataset, a directly fault pattern recognizing procedure in TD can be performed. First, the one-dimension online MEMS inertial measurements are converted to 2-D spectrums using the HHT; Then the 2-D TD features are fed to the trained CNN model as in Fig. 4, then the fault classifications can be obtained.
3. Experiments
We select the temperature-related MEMS inertial sensors faults which are detailed in in Fig. 5 to validate the performance of proposed FD method. The inertial data are sampled in the calibration operation of MEMS inertial sensors of our micro guidance and navigating controllers. The inertial sensors are setting in various temperature environment from -40 °C to 68°C. These characters contain the most cases of temperature-related of MEMS inertial sensors. As in Fig. 5. The dataset in SD, TD and auxiliary dataset are detailed in Table 2.

![Fig 5. The temperature-related MEMS inertial sensors faults.](image)

**Table 2. Dataset configuration**

| Number | Dataset                     | Description                         | Label     | Number of samples |
|--------|-----------------------------|-------------------------------------|-----------|-------------------|
| I.     | **Source domain**           | (For generating auxiliary dataset)  | Labeled   | 5000*4            |
| II.    | **Source domain**           | (For training BLSTM model)          | Labeled   | 1000*4            |
| III.   | **Labeled Target domain**   | (For training BLSTM model)          | Labeled   | 1000*4            |
| IV.    | **Unlabeled Target domain** | (For training CNN)                  | Unlabeled | 20000             |
| V.     | **Auxiliary**               | (For training CNN)                  | Labeled   | 5000*4            |
| VI.    | **Labeled Target domain**   | (For FD performance testing)        | Labeled   | 2000*4            |

3.1. Target Domain Data Set Generating Validation
In this research, we use the simulation model to generate the TD features for testing the performance of proposed TL-based FD method. The online aerial dynamic characters are controlled by the environment model and control loop and the faults in various temperature are injected to the control loop, thus the fused TD fault features are obtained. The TD measurements in cases of different conditions are shown in Fig. 6 which includes one normal condition and three faults conditions. To obtain the robust representation of TD features, EMD operation is performed for getting the IMFs.
3.2. BLSTM-based Feature Transfer Learning Performance Validation

In this section, we have performed the comparison experiment to evaluate the effectiveness of BLSTM-based TL method, we have selected various classifier-based FD methods to compare the fault classification performance, the selected methods are proposed CNN, 1D-CNN [5], ANN [2] and SVM [3]. The selected fault classification models are respectively trained by SD dataset and auxiliary dataset. The comparison item is the classification accuracy in ten times running as in Fig. 7. We can see that the models trained by the auxiliary samples have obtained the obvious better performance than models trained by SD samples.

3.3. Comparison with State-of-the-Art TL Based FD Methods

In this section, we compared proposed TL-based FD method with the other state-of-the-art TL-based FD methods. Firstly, we train the MS-CNN in Fig. 4 using dataset-IV and dataset-V. As obtaining the optimal FD parameters, we compare proposed FD method with state-of-the-art TL-based FD methods which include Xiao et al.’s method [7], Che et al.’s method [8] and Wu et al.’s method [9]. We have compared the classification performance and the confusion matrix between the proposed FD method and compared methods, Fig. 8 details the FD accuracy comparison confusion matrix comparison results. The excellent performance of proposed FD method benefits from the BLSTM-based feature transfer and CNN-based model transfer operations. First, the BLSTM-based transfer learning method offers auxiliary samples which smaller discrepancy with TD samples and the CNN trained by auxiliary samples obtains better initial sates; Second, the CNN-based model transfer learning method further optimize the CNN in a semi-supervision learning process.
4. Conclusion
This paper proposes a TL-based MEMS inertial sensors fault diagnosis method, the proposed method address the insufficient working condition fault samples problem in MEMS inertial sensors FD and enhanced generalization ability of FD model trained by the offline MEMS inertial sensors calibration samples. The excellent FD performance of proposed method is benefited from the auxiliary dataset which has less distribution discrepancy with TD and MMD-based TD samples auto label method. The BLSTM-based auxiliary dataset operating method performs excellent feature transfer performance through the IMF level mapping operation which offers more stable and robust feature representation in SD and TD. The CNN-based model transfer method further enhances the fault classification performance in TD by utilizing MMD based label method. Note that the IMF level transfer learning strategy in our proposed method is in time domain, in future, frequency-domain-based RNN and IMF transfer model can be studied for obtaining more robust feature representation.

Acknowledgments
This work was supported in part by the Natural Science Foundation of China under Grant 61274117.

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