Evaluating Semi-supervised Learning for Automated Fault Detection and Diagnosis of Air Handling Units

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Abstract

Traditional supervised learning based fault detection and diagnosis (FDD) techniques show impressive high diagnostic accuracy in recognizing various air handling units (AHUs) faults.In real-world AHU FDD scenarios, the number of faulty training samples may not be enough to support supervised learning methods, since faults are usually fixed within short periods of time. In this study, a semi-supervised learning FDD framework is proposed to deal with the above problem. By using the proposed framework, the training pool will be enriched by iteratively inserting confidently labeled testing samples, which mimics the scenario of detecting faults the earliest possible. Furthermore, the proposed framework can be easily extended with various kinds of state-of-art classifiers. Three important tradeoffs are observed through a series of experiments. With a reasonably small number of faulty training data samples available, the performance of the proposed semi-supervised learning technique is comparable to the classic supervised FDD methods.

Introduction

Fault detection and diagnosis (FDD) at early stage is mandatory for critical components of heating ventilation air-conditioning (HVAC) systems, such as air handling units (AHUs). An effective FDD method of HVAC subsystems offers proper maintenance of those important components, prevents further damage, maintain indoor air quality and saves 15% to 30% of total energy consumed by buildings (Katipamula and Brambley 2005). As one of the most extensive and important components for a HVAC system, AHU supplies indoor environment with conditioned fresh air with a supply fan and exhausts the return air using a return air fan. The main components of AHU include fans, one cooling or heating coil, ducts and dampers. In general, AHU maintains the indoor air quality, temperature, humidity and indoor comfort. Regular monitoring with automatic FDD technique is highly recommended for AHUs.

Recently, supervised machine learning (ML) FDD methods for AHUs have reported detection and diagnosis accuracy rates as high as 93-98% under different setups (Du et al. 2014) (Mulumba et al. 2015). Research gap exists when most of the AHU faults were fixed immediately once they were detected, resulting in high imbalance of data sizes between normal operational data and faulty data in real-world datasets; and most of the supervised machine learning methods assume equal sizes of the normal and faulty data. A practical FDD method is demanded to detect and diagnose various AHU faults with smallest possible number of faulty samples available.

In this study, a semi-supervised FDD framework is proposed which intends to use the minimal number of faulty samples for training, detects and diagnose possible faults as early as possible for AHUs. Moreover, through a series of experiments, three tradeoffs are observed, which include:

- The tradeoff between the initial number of faulty samples selected in the training dataset and the final classification accuracy.
- The tradeoff between the initial number of faulty samples selected in the training dataset and the number of iterations (computational cost).
- The tradeoff between the threshold of confidently levels and the final classification accuracy.

The experimental results of this study can be useful under two scenarios:

- **Scenario 1** There are a number of faults experienced by a particular AHU; however, the number of training samples for each fault is small, i.e., the faults are always fixed within a short period of time. When another fault occurs, it is unclear that whether a supervised FDD method is able to identify the fault correctly. The experiments of this study suggest the minimal number of faulty training samples for an indicated data-driven FDD method to correctly identify the fault types.
- **Scenario 2** There are absolutely not enough faulty training samples available in the database. When another fault occurs, the building management system (BMS) requires some response time to recursively identify the fault type using the proposed semi-supervised learning framework. New faulty samples can be absorbed into the training data pool with high confidence levels. The experiments of this study suggest the minimal response time for the proposed FDD framework to correctly identify the fault types while there are not enough faulty training samples available in the training pool.

The proposed semi-supervised FDD framework requires a base classifier, which is supposed to be able to diagnose existing fault types efficiently with relatively small quantity training samples available. As a modern machine learning technique and data-driven method, support vector machine (SVM) is employed in many recently published works, and has demonstrated its classification ability in the field of FDD for HVAC subsystems. As a result, we use SVM as a base classifier for the proposed semi-supervised classification framework. The simulation performance shows an over 80% accuracy using a training set consisting of 8,000 normal samples and only around 30 samples for each fault type tested.

Methodology

A semi-supervised data-driven FDD algorithm is proposed to detect and diagnose the AHU faults acquiring only a few faulty training samples. By pre-processing the raw data, including normalization and a feature selection process, the original dataset is converted into a subset containing less feature variables in order to improve the training efficiency. The training pool only a few faulty samples for each fault, i.e., from 5 samples to 55 samples of each faulty dataset, along with a large number of normal data samples, mimicking the real-world early detection scenarios for AHU faults. In the testing phase, we purposely use equal size of normal testing samples (N) and testing samples of various fault types ($F_1, F_2, ..., F_n$). All classified tested samples will be assigned a confidence level after a label is assigned by the classifier. Only those classified samples with strong confidence levels will be assigned a label and inserted into the training pool. The rest testing samples will be classified again using the enlarged training pool. The experimental results simulate the diagnosis accuracy rates under various scenarios, while the number of faulty training data samples differ. The resulting statistics can be significantly useful for real-world applications measuring the number of faulty training samples required to detection specific faults. The overall flowchart of our algorithm is shown in Figure 1.

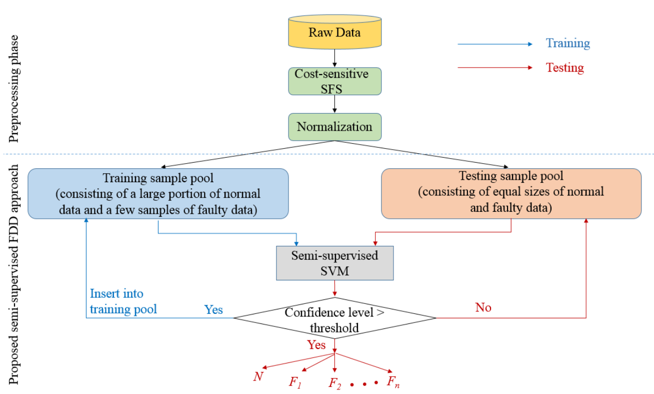

Figure 1: The flowchart of the proposed semi-supervised FDD approach for AHU faults.

Algorithm 1 formally describes the proposed semi-supervised FDD approach for AHU faults. After the preprocessing phase (as stated in Figure 1), the processed original dataset can be divided into training and testing sets, where the training set contains 5, 10, 15, 20, ... or 55 faulty training samples, accompanied with 8,000 normal training samples. The testing set contains around 1,400 faulty testing samples with over 8,000 normal testing samples (the number of samples ratio between faulty testing samples and normal testing samples is 1:1). The entire semi-supervised FDD algorithm is bounded by a while-loop. In each iteration, the SVM model is first trained using the revised training set. Then, each testing sample is assigned a predicted label with a confidence level by the trained SVM model. All testing samples with confidence levels greater than a pre-defined threshold will be inserted into the training set (marked as 'labeled' and will not be tested again); and the predicted labels are treated as actual labels in next round SVM model training. All testing samples with confidence levels less than the pre-defined threshold will be tested again in the next iteration. The whole process terminates when all testing samples are marked 'labeled' or the maximum number of iteration is reached.

Algorithm 1 Semi-supervised FDD Approach for AHU Faults

Input: 1. The training set **TR** contains only a few faulty training samples with a large number of normal training samples. 2. The testing set **TE** contains equal numbers of faulty and normal samples.

Output: Prediction label set **PL** for all testing samples.

```
Initialization: mark all testing samples as 'unlabeled'.
while There are 'unlabeled' testing samples & the number of iteration ≤ the maximum number allowed do
    Train the multi-class SVM model with TR.
    for each 'unlabeled' testing sample x in TE do
        Collect the prediction label l and confidence level δ for x from the trained SVM model.
        if δ ≥ pre-defined confidence level threshold then
            Mark x as 'labeled'.
            Insert tuple (x, l) into TR.
        end if
    end for
end while
```

In Algorithm 1, the semi-supervised SVM is designed to deal with the imbalanced training dataset that contains a large number of normal data samples with only a few faulty samples. Highly confident testing samples with fault types been labeled can be absorbed into the training pool to enrich the faulty training dataset. Once the highly confident testing samples been inserted into the training pool, the parameters of the SVM have to be revised; and the time complexity increases. The number of iteration has to be minimized with reasonable parameter settings, e.g., a suitable confidence level threshold value.

Experimental Results

Data Description

The AHU normal/faulty operational data is collected by The American Society of Heating, Refrigerating and Air-

Conditioning Engineers (ASHRAE) project 1312-RP (Li and Wen 2010). There are in total two AHUs are used in the 1312-RP project. One of them (AHU-A) simulates normal conditional data; and the other (AHU-B) simulates faulty data. On each day, AHU-B generates faulty data samples for one particular fault type. Therefore, each faulty subset generated by AHU-B consists of 1440 data samples (1 day, 1 minute per sample), and is accompanied by a corresponding normal dataset that is generated by AHU-A. In this study, we select six typical faults from the faulty dataset to perform multi-class classification and enumerate them from F1 to F6: (F1) Exhausted air (EA) damper stuck (fully open), (F2) Return fan at fixed speed, (F3) Cooling coil valve control unstable, (F4) Cooling coil valve partially closed (15% open), (F5) OA damper leak and (F6) AHU duct leaking (after supply fan (SF)).

Together with the normal operational data type, the multiclass fault diagnosis becomes a 7-class classification problem. There are in total 21,600 normal operational data, accompanied with 1440 faulty samples for each fault. For each experimental simulation, the initial number of normal data samples in the training pool is around 8,000; and the initial number of faulty data samples in the training pool is from 5 to 55. The rest of the data samples are treated as testing samples.

Results

In this section, we answer the three questions raised in the Introduction, which are the three tradeoffs between the number of initial faulty training samples, FDD accuracy and confidence level threshold selection. The proposed semi-supervised SVM is compared with existing modern semi-supervised methods, including semi-supervised extreme learning machine (ELM) (Huang, Zhu, and Siew 2006), decision tree (CART) (Rutkowski et al. 2014), k-nearest-neighbor (KNN) (Peterson 2009) and random forest (RF) (Liaw, Wiener, and others 2002). The fairness of experimental result comparison is guaranteed by 30 times repetition of each experiment.

The experiments were performed on a standard lab machine with Intel Quad Core i7-7700, 8GB RAM and 1T SSD hard disk. We implement four state-of-art semi-supervised methods and compare the FDD accuracy with the proposed semi-supervised SVM method. The semi-supervised SVM implementation can be easily extended to other semi-supervised methods by replacing the SVM in Figure 1 with other classic machine learning models, such as KNN, CART, RF and ELM. The classification accuracy rates for various numbers of initial faulty samples in the summer season are listed in Tables 1. It is noted that each accuracy rate is an average rate over 30 times repetitive simulations.

Figures 2 show the FDD accuracy rates of the five semi-supervised machine learning methods in the summer season. The proposed method is able to achieve over 80% accuracy rate with only 30 initial faulty training samples for each fault type. Moreover, while the number of initial faulty samples keeps increasing, the FDD accuracy tends to be stabilized and approaches to the classification accuracy of supervised learning. From Figures 2, suggestion can be made that the minimal number of initial faulty training samples for an effective semi-supervised AHU FDD is around 30 for each fault type.

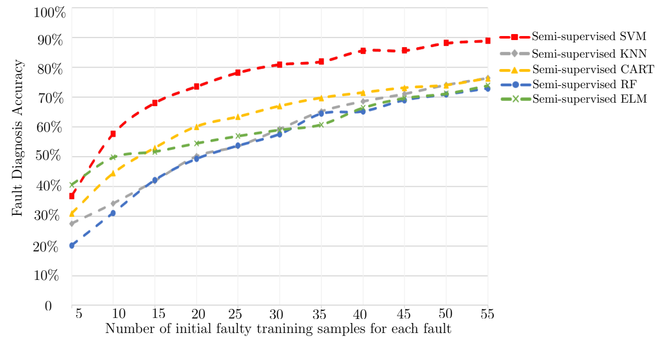

Figure 2: Experimental results comparison between various semi-supervised machine learning methods in summer season.

The second tradeoff concerns about the computational complexity of the semi-supervised algorithm. The actual time consumed by each method depends on the hardware configuration of the machine. For modern machine learning tools, such as SVM, ELM, KNN, CARt and RF, the training time for a medium size dataset with less than 10,000 data samples is less than 5 seconds. Therefore, in this subsection, we only show the number of iterations (training processes) for each compared semi-supervised method(Tables 2).

An appropriate confidence level threshold maximizes the semi-supervised SVM classification accuracy and also increases the overall FDD efficiency. In this study, we select the confidence level thresholds by investigating the highest classification accuracy versus various threshold values with different initial faulty training sample numbers in the training subset. For training subsets with 10, 20, 30, 40 and 50 initial faulty samples for each fault type, the optimized confidence level threshold is always from 0.9 to 0.95, which suggests that only highly confident testing samples can be inserted into the training pool in order to maximize the overall FDD accuracy. Figure 3 depicts a general relationship between confidence level thresholds and averaged diagnostic accuracy for AHU faults using 10, 20, 30, 40 and 50 faulty training samples in the training dataset for the summer season dataset.

Conclusion

Traditional supervised machine learning techniques showed an impressive high diagnosis accuracy for various HVAC faults. However, research gaps exist while there are not enough training data from the fault types in real-world industrial applications. Two questions arise: 1) How do we apply existing supervised machine learning methods to cases when there are not enough faulty training samples? 2) How many faulty training samples are called 'enough' to make accurate FDD predictions?

This study answers the above two questions and fills an important gap between traditional theoretical supervised

Table 1: The FDD accuracy rates (%) for various semi-supervised learning methods based on different numbers of initial faulty samples in the summer season.

# Init. fault.	5	10	15	20	25	30	35	40	45	50	55
Semi-SVM	36.82	57.67	68.07	73.58	78.27	80.99	81.96	85.64	85.70	88.18	88.96
Semi-KNN	27.5	34.26	41.84	50.13	53.54	59.32	65.27	68.62	71.14	74.15	76.43
Semi-CART	30.88	44.38	52.91	60.09	63.37	66.98	69.73	71.48	73.11	73.99	76.29
Semi-RF	20.18	31.1	42.12	49.25	53.68	57.58	64.43	65.20	69.01	70.91	72.95
Semi-ELM	40.57	49.75	51.67	54.48	56.93	59.01	60.78	66.44	69.70	71.20	73.94

Table 2: The number of iterations (computational complexity) for various semi-supervised learning methods based on different numbers of initial faulty samples in the summer season.

# Init. fault.	5	10	15	20	25	30	35	40	45	50	55
Semi-SVM	12.3	12.7	19.0	16.8	22.7	27.1	28.6	25.4	23.0	26.0	21.4
Semi-KNN	6.7	6.8	7.1	7.3	7.5	8.7	10.3	8.8	10	11.2	11.6
Semi-CART	4.4	4.8	5.1	5.3	5.0	5.2	5.4	6.0	5.0	5.7	7.3
Semi-RF	7.4	9.5	16.0	15.8	19.7	33.8	41.5	40.4	49.6	61.1	68.1
Semi-ELM	16.3	13.7	20.1	38.4	38.2	45.6	52.2	56.8	58.3	65.1	80.2

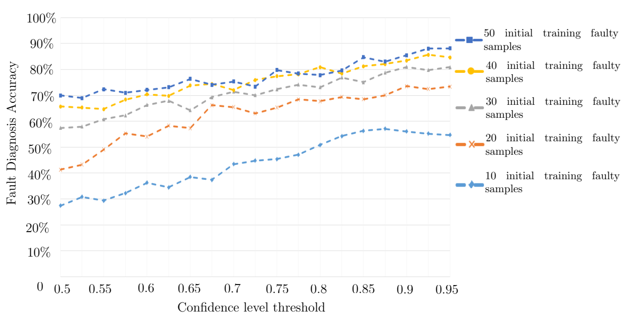

Figure 3: Experimental results showing the averaged diagnostic accuracy rates versus various confidence level thresholds.

FDD methods and practical FDD applications for various AHU faults. The proposed semi-supervised SVM solves the above problem and demonstrates the classification performance with between 80% and 89% accuracy rates using a training set consisting of 8,000 normal samples and only 30 samples for each fault type. Experiments are performed with different numbers of initial faulty training samples to show the minimal number of faulty samples required to diagnose a particular fault. There are also suggestions provided about the most appropriate confidence level threshold balancing the tradeoff between classification accuracy and efficiency. The proposed semi-supervised FDD framework can be easily extended by replacing the SVM with other modern machine learning techniques.

Future work of this study includes using generative adversarial networks (GANs) to perform unsupervised learning on various faults of AHUs and turns the traditional supervised approaches for FDD on HVAC systems completely to unsupervised learning. The generated samples from GANs will be evaluated using semi-supervised learning method proposed in the current study.

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