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A Novel Way to Apply Transfer Learning to Aircraft System Fault Diagnosis

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ABSTRACT

In recent years, transfer learning as a method that solves many issues limiting the real-world application of conventional machine learning methods has received dramatically increasing attention in the field of machine fault diagnosis. One major finding from an initial literature review shows that the majority of the existing research only focus on the transfer of diagnostic knowledge between various conditions of the same machine or different representation of similar machines. The primary goal of the current work is to seek a way to apply transfer learning to distinct domains, thereby expanding the boundary of transfer learning in the fault diagnosis field. In particular, attempts will be made to explore ways of transferring knowledge between diagnostic tasks of different aircraft systems. One promising method to help achieving this goal is transfer learning by structural analogy, since this method is capable of extracting high-level structural knowledge to apply transfer learning between seemingly unrelated domains, similar to the scenarios of transfer between different aircraft systems.

1. MOTIVATION AND RESEARCH PROBLEM

Transfer learning has recently been a popular research topic in the field of Intelligent Fault Diagnosis (IFD). As Lei, Yang, Jiang, Jia, Li, and Nandi (2020) pointed out, transfer learning is the promising method to "expand IFD from academic research to engineering scenarios". Its capacity to overcome the various factors that render conventional machine learning algorithm inaccurate or inapplicable in the diagnosis of real-case machines had recently attracted a great deal of attention in the academic world, which is demonstrated by the dramatic increase in the number of publications on applying transfer learning to IFD in the recent three years. Therefore, this work aims to investigate this exciting new research trend and to develop a novel transfer learning method to apply to aerospace systems.

The initial literature review had discovered that, in the field of IFD, most existing research focus on applying transfer learning only between similar tasks, in which low-level similarities such as the data structure and the physical parameters are required to be the same. This work will attempt to expand the boundary of transfer learning method by addressing more distinct domains of transfer, where low-level similarities can no longer be depended on. Specifically, the research problem was determined to be designing a novel method that achieves knowledge transfer between the diagnosis of different aircraft systems.

2. LITERATURE REVIEW

To collect relevant literature, a keyword search of "transfer learning" with "machine fault diagnosis" was conducted on Scopus in November 2021, which returned 412 publications. A similar pattern was discovered when analysing the research trend of the first 70 and second 70 entries, hence these 140 entries were decided to be adequate to represent an overview of the field of applying transfer learning to IFD.

2.1. Research motives

The top four motives for conducting the research as stated in the publications are: 1) to solve small sample problems; 2) to solve the lack of labelled samples; 3) to overcome the shortage of faulty data; 4) to adapt to the data distribution discrepancy over the domains of concern. This is consistent with the theory that transfer learning is fundamentally introduced to overcome the limitations of conventional machine learning methods (Yang, Zhang, Dai, and Pan, 2020).

In the field of IFD, conventional machine learning methods would only perform accurately if the training data met all four requirements simultaneously: 1) are in sufficient quantity; 2) have sufficient labelling; 3) are balanced; 4) display the same distribution pattern as the testing samples.

However, real-world machines rarely produce such ideal training samples, hence it has motivated researchers to apply transfer learning to IFD.

2.2. Application fields and validating examples

The fields of application showed a high concentration on bearings and gearboxes, which respectively took up 57% and 15% of the research studied. A further inquiry into the validating examples was conducted in this work and discovered that 85% of the bearing research referred to, in their method validating process, the same bearing dataset published by Case Western Reserve University (CWRU). The lack of diversity in the fields of application and the high dependency on the same validating dataset raised the concern on whether many existing transfer learning-based IFD algorithms could have good generalization capacity over alternative applications.

The other 28% of research focused on various applications such as transformers, wind turbines, induction motors and so on. Since this work aims to apply transfer learning to aerospace, a search for all aerospace-related research within the 140 publications, and all other entries outside the 140 results on Scopus, was performed. This found examples only existed in the fault diagnosis of spacecraft attitude control system, aero-engine gas path, electromagnetic actuators, aircraft fuel pump, UAV inertial sensors, quadrotor, and commercial flight data. Therefore, there are numerous opportunities to apply transfer learning in aerospace IFD, and to do it across the diagnosis of different aircraft systems is among such research gaps.

2.3. Domains of transfer

Another important aspect of research gathered for the 140 papers is the selection of the source and target domains between which the transfer happens. Overall, most research only discussed transfer between similar domains. As statistics showed, 55% of the research discussed transfer between the diagnosis of the same machine under various working conditions that either involve a selection or a combination of varied load, rotational speed or degradation level. Another 27% of the research was on the transfer between different representation of the same machine - either between a lab-scale test rig and the real-size machine, between simulation and real data or between slightly different sub-type of the same machine.

Although the majority of transfer learning work in IFD only considered transfer between similar domains, some attempts were made to push the boundary of transfer. For instance, one common assumption when applying transfer learning to IFD is that the target domain label space must be either identical to, or a subset of, the source domain label space (Lei et al., 2020). Li, Huang, He, Wang, Li, and Li (2020) attempted to break this assumption by introducing a new fault type in the target task that is not present in the source domain samples. Li et al. (2020) chose both the source and target domain samples from the CWRU dataset, but the target domain samples were taken at different load and speed with outer race fault chosen as the additional fault type than the source domain. Li et al. (2020) managed to handle the difference in the label spaces by introducing a pseudo decision boundary after the feature extraction stage that distinguishes the new emerging fault from known fault classes. Pushing the transfer boundary ever further, Deng, Huang, Du, Li, Zhao, and Lv (2021) considered the transfer on different machines (TDM) by partial transfer with different faults. Deng et al. (2021) designed a double-layer attention based adversarial network which essentially conduct domain adaptation in a discriminative way to minimize the negative effect from irrelevant source data. This method by Deng et al. (2021) demonstrated the ability to transfer diagnostic knowledge between different types of bearings under different working condition with different damage modes and display different damage characteristics, all at the same time.

Inspired by these attempts, this work has proposed the idea to push the boundary of transfer even further by seeking a way to transfer diagnostic knowledge not just between different machines, but between distinct machines, such as different aircraft systems.

3. Proposed Approach

3.1. The inspiration from the history of transfer learning

Transfer learning, being a machine learning paradigm as it is seen today, has a historical root in transfer of learning in the field of cognitive science (Yang et al., 2020). Transfer of learning studies the phenomenon that “humans can draw on the past experience to solve current problems very well (Yang et al., 2020)”.

One way how transfer of learning evolved to transfer learning originated from the biological aspect of human learning. As Bozinovski (2019) pointed out, the earliest mathematical model on transfer learning was based on neural networks. This finding explains why most transfer learning method commonly seen are heavily network-based.

However, current assumptions of the common transfer learning methods restrict applications to different but similar tasks, which cannot accommodate the goal of this work. As a result, this work had focused on how the other aspect of transfer of learning, the conceptual aspect of human learning, might have contributed to transfer learning. The reason for this shift in focus is that humans are capable of resolving high level similarities to learn seemingly unrelated tasks (Yang et al. 2020). Transfer learning that captures this high-level transfer is in line with the goal to achieve transfer between more distinct domains. The next sub-section gives one method that bears some promising features to this work’s research problem.

3.2. Introduction to transfer learning by structural analogy

Transfer learning by structural analogy is a type of relation-based transfer learning method. Unlike other relation-based transfer learning method, it is unique in the way that analogues are found in the domains of interest as the output of the algorithm. Consequently, analogues found in the seemingly unrelated domains work as the bridge that achieves the knowledge transfer which is otherwise considered impossible.

Wang and Yang (2011) designed such algorithm that achieves transfer where the source and target domains have completely different representation spaces. Since there is the absence of low-level similarities for such transfer scenario, Wang and Yang (2011) first introduced a mapping of the features from both domains into the Reproducing Kernel Hilbert Space (RKHS), where the structural dependencies of the features can be estimated. By maximizing the dependencies between the features and the labels in both domain as well as between the features across the two domains, features that bear analogical value, and also help to establish the correct labels, are identified (Wang & Yang, 2011). Wang and Yang (2011) used a medical diagnosis dataset to validate the analogy found by the algorithm, where after the algorithm identified ten pairs of analogical terms in the diagnosis of cardiovascular diseases and respiratory tract diseases, by treating the analogues in both domains equivalent, the classifier trained in the source task yielded 80.5% accuracy in the target task.

This work considers this algorithm as a promising approach for the problem of transferring diagnostic knowledge between different aircraft systems, since abundant structural relations exist in aircraft system data. Adaptation of the method will be necessary for this application. For example, if analogues of features in the symptom vectors of two aircraft systems can be found, by treating them as equivalents, transfer of a pre-trained classifier could be effectively implemented.

4. Applications and Contributions of the Work

Applying transfer learning to aircraft system fault diagnosis is a promising way to enhance the smart diagnosis process. Upon successful transfer of diagnostic knowledge across different aircraft systems, the robustness and accuracy of the diagnostic model are expected to be benefited.

This work will contribute to the progress in the field of condition-based maintenance (CBM) and integrated vehicle health management (IVHM). If the ambition of transfer learning between distinct machines is achieved, the common belief in the boundary of transfer learning would be largely expanded.

5. Work in Progress

Surrounding the thesis on applying transfer learning in the field of aircraft fault diagnosis, the author has only reached the last stage of his initial literature review and is currently drafting a literature review paper. The paper will discuss the importance of adopting machine learning and transfer learning method in aircraft fault diagnosis, an investigation into the transfer learning method, an overview of the existing research of applying transfer learning to IFD, and the proposed method to resolve the research problem identified in the research gap. However, there has not been any experimental work to execute the method proposed at the current stage.

6. Conclusion

Focusing on the topic of applying transfer learning to the diagnosis of aircraft, this work has discovered research gaps in applying the transfer learning method to aircraft systems and between transfer domains that are more distinct. Inspired by the investigation into the history and the whole spectrum of transfer learning methods, a possible route to address the main research problem of transferring diagnostic knowledge between different aircraft systems is identified to be applying transfer learning by analogy, which could potentially push the boundary of transfer learning in IFD.

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