Transfer Learning Algorithms in Unmanned Aerial Vehicle Networks: A Comprehensive Review

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ABSTRACT

Due to the high manoeuvrability and low cost, unmanned aerial vehicles (UAVs) have appeared as a promising candidate for various applications such as surveillance, reconnaissance, target tracking, and UAV imagery. As data-driven and delay-sensitive applications bring new challenges in UAV networks, machine learning (ML)-based techniques have grabbed significant research attention with the capability of smart training and intelligent decision making. However, owing to the limited battery lifetime, training traditional ML algorithms brings a huge burden on the UAV networks. Furthermore, every task-specific scenario needs a specific tailored model to be designed with shorter training time and faster decision-making capability. To tackle these challenges, transfer learning (TL) has recently appeared as a potential solution. The basic idea of TL is to utilize knowledge gained from similar tasks and reuse them into a new problem to enhance the learning efficiency of the new problem. In this paper, we present a comprehensive survey on TL algorithms in UAV networks. After addressing a brief overview of TL, we discuss the exiting TL algorithms in UAV networks. We then compare the different TL algorithms in terms of the application area, main idea, innovative features, advantages, and limitations. Open issues and research challenges are also discussed.

KEYWORDS

Unmanned aerial vehicle, unmanned aerial vehicle network, transfer learning, transfer learning algorithm, training time

1 INTRODUCTION

The recent advancement of the Internet of things and wireless communication technology have brought together a wide range of delay-sensitive and data-driven applications. Even though ground infrastructure-based architecture has enormous computing capacity to execute such computing tasks, the presence of obstacles such as high rise buildings and limited communication capabilities degrades the overall task execution efficiency [1].

In this context, unmanned aerial vehicles (UAVs) have emerged as a promising solution that can mitigate the above problem. Due to their high maneuverability and dynamic mobility, UAVs can fly anywhere and provide line-of-sight communications, extend coverage beyond terrestrial infrastructure, and provide computing and relay services [2]. However, due to the dynamic environment characteristics, UAVs may need to perform both sensing and computing services which severely degrade the overall mission performance. In this context, machine learning (ML) techniques as a smart and powerful framework allows UAVs to smartly sense the time-varying dynamics of environments and make intelligent decision based on task requirements. This is possible due to the ability of ML to generate rules from huge data and prediction capability. For example, utilizing a reinforcement learning (RL) technique, an agent can smartly act in an environment with dynamic characteristics and take intelligent decision in an unknown environment to obtain a common goal [3], [4]. However, because an agent needs to learn from the very start, this incurs long training delay and affects the limited battery of the UAVs.

To tackle this challenge, transfer learning (TL) is a potential solution in UAV networks due to its efficient learning and knowledge sharing capability [5]. Compared to other traditional ML technique, TL can utilize the learned knowledge from similar tasks and reuse them to enhance learning efficiency. Thus, TL provides several benefits such as providing enough training data, enhanced learning procedure, and computing efficiency. Because UAVs have a limited capacity of battery lifetime and computing energy, TL can be a very promising solution in a sense that UAVs can reuse the knowledge gained from other UAVs acting in similar environments or performing similar tasks. This would require lower training time and increase learning efficiency in comparison to training a model developed from scratch.

Although TL provides a wide range of benefits in UAV networks, there exist some drawbacks. For example, how to choose source task and target task is one of the major performance factors in TL. Selecting the source task as well as what knowledge to share is one of the most important factors while designing a TL algorithm. Thus, transferring only the useful information can be of huge importance [6].

In this paper, our goal is to provide a comprehensive survey on the TL algorithms in UAV networks. First, we provide a background study on TL to provide a basic understanding of TL in UAV networks. Next, we discuss the TL algorithms applied in UAV networks in association with their applications. Then, we compare the TL algorithms in terms of application area, main idea, innovative features, advantages, and limitations. Finally, we provide some key issues and research challenges to motivate further study in this field.

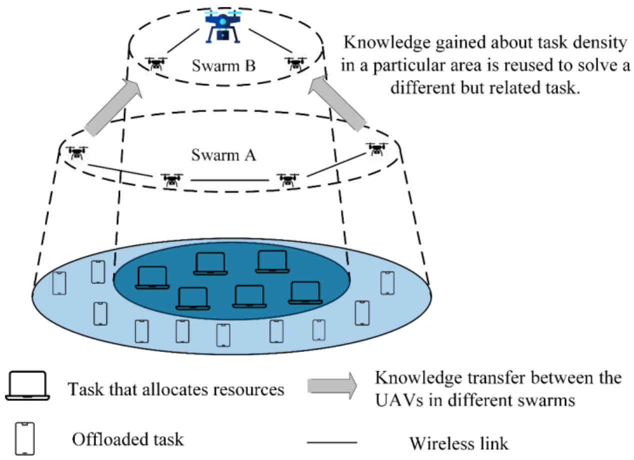

Figure 1: An example of a UAV network utilizing transfer learning.

The rest of this paper is organized as follows: In the following section, basic background is summarized and reviewed. In Section 3, the TL algorithms applied in UAV networks in association with their applications are technically reviewed. It is investigated how the TL algorithms are effectively applied to the various application areas of data collection, vehicle tracking, security, spectrum management, aerial computing, and trajectory design. In Section 4, the TL algorithms are qualitatively compared and discussed. In Section 5, key open issues and challenges are summarized. Finally, we conclude this paper in Section 6.

2 BACKGROUND

In this section, the basic concepts of transfer learning and its application in UAVs are overviewed in brief as the fundamental background of this survey.

2.1 Transfer Learning

As mentioned earlier, TL is one of the most promising solutions to solve the problems more effectively compared to traditional ML techniques. The intuition of TL comes from the concept of using learned knowledge at the past in a new scenario. Based on this idea, TL enables to share and reuse the knowledge of existing one or more tasks, which significantly improves learning efficiency and reduces training time for a new task. The existing and new tasks are usually referred to as source task and target task, respectively.

The criterion for sharing knowledge depends largely on what domain the tasks are and how much similarity exists between the two tasks. These two domains can either be the same or somewhat different from each other. For example, in the case of UAVs, an agent UAV gained knowledge of task density for designing a task offloading technique can be reused while designing a new approach for resource allocation. This is because the two domains are somewhat similar but different as shown in Figure 1. Thus, the new agent does not need to be trained from the scratch and thus the learning is efficient. In addition, the lack of data, the insufficient number of samples, and poor labels are major issues during training any ML algorithms on an agent. In such context, TL enables the reuse of past experiences in the new environment, which allows to make use of other data that are available externally. These are the major advantages of using TL over traditional ML techniques [7].

The formal definition of TL states that, provided a source task T_s with an associated source domain D_s and a target task T_t with an associated target domain D_t, the main objective is to determine the target predictive function W_t through utilizing the knowledge obtained from D_s and T_s where $D_s \neq D_t$ or $T_s \neq T_t$ [8]. Here, not only the source domain and source task but also the target domain and target task must be different from each other in order to apply TL. Otherwise, the problem would become conventional ML problem [8]. According to the definition of TL, the three crucial points of TL are what, when, and how to transfer. "What to transfer" refers to the information that is transferred between the different domains. After determining what knowledge should be transferred, algorithms must be designed so that the transfer ensures the effective learning. The second issue asks for the appropriate situation when the knowledge should be transferred and not. Failing to do which would cause an unsuccessful transfer is generally referred to as negative transfer. After deciding the knowledge type and the time to transfer, the final key point is to decide how the knowledge sharing should happen. This often refers to optimizing the transfer efficiency of the model.

2.2 Transfer Learning in UAVs

The emerging advancement of UAV technology enables a wide range of applications such as aerial access networks, which includes disaster recovery, surveillance, reconnaissance, and aerial imagery [9]. This also brings about new challenges in the UAV domain. Due to the limited battery lifetime, there are various design factors that may affect the mission performance. For example, when UAVs are deployed in a new environment, there is the lack of data with regard to using ML techniques. In such an environment, UAVs need to process and transmit the data along the not-optimized trajectory which degrades the overall mission performance. Although smart ML techniques are being utilized to enable the UAV to take intelligent decisions, the lack of data can cause inefficient training performance. Also, RL approaches (which are being widely used nowadays) requires longer training time to converge.

In this context, TL is a promising solution that can provide an effective learning experience for UAVs. Because TL makes the pathway to reuse (or share) the gained experience and knowledge from one domain to another, UAV as an agent can receive knowledge and experience from similar environments in a multi-UAV mission. Such a strategy helps to find the optimal strategy. In many cases, the scenarios are new and thus the lack of data is another challenge that researches face during designing an algorithm. In other words, TL enables to reuse data from similar environment which solves this problem efficiently. Thus, compared to the conventional ML techniques, TL is going to be the next emerging technology for finding solutions of the emerging UAV networks

3 TRANSFER LEARNING ALGORITHMS IN UAV NETWORKS

In this section, we review various TL algorithms in UAV networks. The TL techniques reviewed in this survey are chosen based on the diverse application areas of TL in UAV networks. We discuss each of the algorithms with respect to the main objective, application scenario, and innovative features in UAV networks.

3.1 Deep Dueling Double Q-Learning with Transfer Learning (D3QL-TL)

Controlling the speed of UAVs is one of the challenging issues to ensure optimal flight performance while performing any mission (e.g., data collection). In a data collection scenario, UAV speed needs to be maintained with respect to various criteria such as distance between sensor nodes and the UAV, data collection period, and sensor node density.

Utilizing the RL algorithms are being widely used, which can consider the large state space problem. However, these algorithms take long time to converge and thus is inefficient for deploying these algorithms in UAVs with limited battery. To tackle this challenge, TL has been introduced which enables UAVs to learn from the experience of other UAVs deployed in the similar kind of environments. This results in reduced training time. In [10], the authors demonstrated a framework utilizing transfer TL where the UAV can jointly optimize speed and battery replacement task by sharing the learned knowledge between UAVs acting on the similar environment to enhance the network performance through reducing the learning time for UAV-assisted IoT data collection.

3.2 Improved Convolutional Neural Network (CNN) and Transfer Learning (CNN-TL)

The application of UAV imagery has gained significant research attention recently due to the ease of use and high maneuverability of UAVs. In addition, the cameras placed at fixed location fail to capture the whole area. UAVs having the capability to fly towards any direction and capturing high quality images with onboard cameras make them a suitable candidate to be considered greatly. The main challenge in UAV imagery applications is the limited battery lifetime of UAVs, which is easily drained because of the computation-intensive deep learning algorithms running on board. Also, the amount of data is not always sufficient.

To tackle the challenge, the authors in [11] proposed a TL-empowered convolutional neural network (CNN) technique for tracking vehicles via aerial vehicles. They identified the problem of poor feature quality and overcame it using TL to pre-train the CNN. Specifically, the weights of the original training model are fine-tuned so that the feature quality is improved significantly. The target model is considered as the target domain and the TL model is considered as the source domain. Thus, the CNN model extracts deep feature maps from the input images and utilizes the high-level features. Afterwards, the target vehicle motion model is constructed, which refers to the time-varying change process of the target. Finally, the tracking process ends by calculating the similarity between the target model achieved and the candidate model defined as the motion recorded at the initial moment.

3.3 Deep RL-Based UAV Relay Scheme (DRLUR)

Security is another major issue in UAV communication. During the communication, the information can be very sensitive and subject to user's privacy which is targeted by the attackers. In particular, the attackers either intend to create communication blockage by transmitting jamming signals or execute denial-of-service attack. To tackle such challenges, the authors in [12] considered a scenario where a mobile user transmits a real-time message (e.g., augmented reality game) to the server. If the base station assigned to the user is jammed, the UAV can relay the user message by adjusting the transmit power. To obtain this, the authors demonstrated a RL based technique which can adjust the relay power to tackle against jamming signals. Particularly, this study leveraged DQN algorithm where they considered previous user's bit error rate, UAV's received jamming power, and the channel gain between the user and base station as the state space. The UAV then selects the ideal transmit power to relay the message.

The advantage of using a RL-based technique allows the UAV to adjust the transmit power without having to know the any prior information about the cellular topology, the message creation technique, jamming, and server computation information. A convolutional neural network (CNN) is utilized to predict the Q-values which is then used by UAVs in combination with the state to select the optimal relay policy. Because initial exploration may take a lot of time which causes slower convergence, a lightweight TL technique is used to adjust the initial weights of the CNN based on the experiences gained in past relay and anti-jamming scenarios.

3.4 Random Forest and K-Nearest Neighbor Based on Transfer Learning (RF-KNN-TL)

Spectrum management is one of the major performance indicators in UAV networks due to high mobile nature. Because most of spectrum management tasks need to be completed within a stringent deadline, both the decision regarding bandwidth requirements and the channel assignment decision in a UAV network must be made faster compared to ground network to ensure seamless connectivity.

A TL technique was demonstrated in [13] for predicting the delay spread and path loss in a UAV communication system using the two machine learning techniques of random forest algorithm and K-nearest neighbors. For training purpose, it is considered whether there is any buildings between two UAVs and the UAV's location coordinates as the feature. Because there is the lack of data in a new scenario, the authors leverage TL technique to reuse experience in a new environment. In particular, the authors proposed two different strategies which are scene-specific TL and frequency-specific TL. In scene-specific TL, the ML models are transferred using the same frequency but trained at different scenarios, whereas the frequency-specific scenario trains the model using different frequencies and transfer to the target frequency. In both techniques, target model receives the weights from the pre-trained model and utilize them to fine tune the target model on the target task data. The authors conclude that root mean square error obtained from the two schemes are significantly lower than the traditional techniques.

3.5 Transfer Learning Empowered Deep Reinforcement Learning (DRL-TL)

Aerial computing is a new paradigm that have emerged as a promising solution for executing applications that are both delay-sensitive and computation-intensive. This phenomenon can provide real-time services on the air. In addition, UAVs can provide better computing services with lower delay compared to traditional computing such as cloud computing and edge computing. However, this phenomenon has some drawbacks too. In an unknown environment, training ML (e.g., RL) algorithms in UAVs incurs longer training time and drains battery, which affects mission performance.

To tackle the challenge, the authors in [14] leveraged a TL approach which can reduce the training time significantly by allowing to obtain prior experience from other agents that have acted on the similar environments previously. This experience transfer enables to reuse and share knowledge among agents. Specifically, the authors consider a scenario where computation-intensive tasks are generated continuously to be processed by UAVs. The study aims to maximize the offloading utility that is obtained for the reduced amount of delay compared to the maximum delay tolerance. To achieve this, the authors proposed a TL-empowered RL technique for achieving effective computation and communication resource allocation by maximizing the offloading utility. To find a solution, the problem is first formed as a Lagrangian multiplier and then the multiplier is iteratively updated. Through extensive simulation, the authors show that utilizing TL maximizes the offloading utility by optimizing the computing and communication resource through sharing knowledge from other UAVs.

3.6 Transfer Learning Integrated Double Deep Q-Learning (DDQN-TL)

Trajectory design is another crucial problem faced in UAV networks. For various purposes such as emergency communication, IoT data collection, and surveillance mission, the trajectory design plays a crucial role behind successful mission performance. To deal with the dynamic environment, RL algorithms have emerged as a promising solution to be implied on UAVs because these algorithms enable to learn the optimal policy in an unknown environment and gradually improving that policy.

In [15], the authors proposed a trajectory design algorithm leveraging the double deep Q-learning (DDQN) algorithm. In particular, the authors consider post-disaster scenarios where the network dynamics are unknown. The UAV aims to find the optimal trajectory on the basis of the received feedbacks from the environment so that the communications network can be reestablished. To speed up the proposed DDQN algorithm, the authors considered the information of the disaster area before and after the disaster as two tasks. Thus, utilizing the user density and geographical characteristics before the disaster is utilized to pre-train a deep neural network. As a result, this pre-trained model is easily deployed into the new post disaster scenario through backpropagation technique by transferring the weights to the new task. This can significantly reduce the interaction with the environment and speed up the learning process as well. This brings adaptivity in an unknown environment.

4 COMPARISON

In this section, we compare the studied TL algorithms qualitatively in a tabular manner. Table 1 shows the comparison between existing TL algorithms in terms of application scenario, main idea, innovative features, advantages, and limitations. As mentioned earlier, existing ML techniques incur long training time which affects the UAV mission performance. Thus, optimizing the mission performance and enhancing the learning efficiency are the major goals of TL. In addition, another challenge is to extract important information from the data, which gets even more complicated when there is the lack of data. In such cases, TL helps to reuse data from similar environments and enhance model accuracy

As shown in Table 1, each TL algorithm was developed for its own application area and has distinctive characteristics. In D3QL-TL [10], the authors mainly aim to capture the dynamicity and uncertainty of UAV networks via using the hybrid technique. Although RL techniques can handle the large state and action space, utilizing TL can make the system more efficient and robust by enabling the knowledge sharing. TL can also improve the feature extraction capabilities of CNN as shown in [11]. Here, the authors address the poor feature extraction characteristics of CNN and utilize TL to improve the features so that the model can be trained with the improved features to better detect the vehicles. Thus, TL can be incorporated into another technique to bring the robustness and efficiency of the algorithm. In addition, TL can be leveraged to set the initial weights of deep learning models to accelerate the training speed as shown in DRLUR [12]. Since the traditional deep learning techniques need significant amount of time initially to train, the authors fill this gap using TL by assigning the weights from a pre-trained model initially. As a result, the learning speed is enhanced greatly.

On the other hand, in RF-KNN-TL [13], the authors observed that, for a reliable UAV communication, the prediction of path loss and delay spread becomes challenging due to the limited amount of data. In such cases, TL is leveraged by training a model using historical data and later utilizes that model to predict the path loss and delay spread where limited data is available. Unlike previous techniques, this is another major advantage of using TL when there is little or no data available. In DRL-TL [14], the authors focused on optimizing the computing and communication resources of UAVs by enabling the environment knowledge sharing between heterogeneous agents. Thus, the training delay is significantly reduced due to the initial knowledge received from other agents. For almost similar purpose, in DDQN-TL [15], the authors incorporate TL with DDQN to enable the UAV to enhance the trajectory acting in the post-disaster scenarios.

Because the unknown environment dynamics can prolong the search and rescue operation in a post-disaster scenario, any initial knowledge about the environment can help the UAV to reduce the training time and increase the search and rescue efficiency. Here, TL enables the UAV to learn the prior knowledge to reduce the interactions with the environment.

Most existing studies consider that no prior information is available to the agent, which is somewhat similar to the practical environments. However, more decision metrics need to be taken into consideration such as high-speed UAV mobility and weather/wind conditions.

Table 1: Comparison of transfer learning algorithms in UAV networks

Algorithm	Application area	Main idea	Innovative features	Advantages	Limitations
D3QL-TL [10]	Data collection	Considers the joint optimization of UAV speed and energy replenishment to maximize the system performance for data collection.	Utilizes TL to reduce the training time by half compared to traditional techniques.	System performance is improved significantly in terms of data collection and energy efficiency.	High computational complexity.
CNN-TL [11]	Vehicle tracking	Proposes a vehicle tracking algorithm utilizing CNN and TL approaches.	Utilizes TL to improve the extracted feature quality of CNN.	Proposed algorithm can obtain tracking accuracy up to 92%.	Does not consider any high-speed tracking scenario.
DRLUR [12]	Security	Demonstrates an intelligent relay power selection approach using RL to tackle against jamming attacks.	Proposed approach does not need any prior information about network topology and computation model.	Significantly reduces the bit error rate and minimizes UAV energy consumption.	Safe exploration for finding the relay policy is not considered.
RF-KNN-TL [13]	Spectrum management	Demonstrates a ML-based prediction method for predicting delay spread and path loss in millimeter-wave channels for space-air-ground networks.	Proposes a feature selection technique and utilizes TL to enhance prediction accuracy.	Proposed approach can reduce root mean square error compared to other methods.	Prediction accuracy can be further improved.
DRL-TL [14]	Aerial computing	Designs a smart aerial edge network which utilizes artificial intelligence technique to determine effective resource allocation strategy.	Incorporates RL and TL together for finding the optimal resource scheduling strategy as well as designing an efficient knowledge sharing policy.	The learning is efficient and the convergence is faster.	Does not consider the effect of high mobility of UAVs on the knowledge sharing. No method how the knowledge should be spliced to share valuable knowledge.
DDQN-TL [15]	Trajectory design	Designs a trajectory planning scheme for UAV-aided emergency communication leveraging DDQN approach.	Utilizes TL technique to reduce the convergence time of RL.	UAVs can adapt more rapidly due to the introduction of TL technique.	Single-UAV system cannot conduct large mission.

5 KEY ISSUES AND CHALLENGES

In this section, we provide some key issues and research challenges to motivate further research in this field. Because TL is potentially a new paradigm, there still remains several challenges.

5.1 Designing Effective TL Framework Using Meta-Learning

What and when to transfer the knowledge are one of the most major issues of using TL approaches in UAV networks. Transferring only the important knowledge selectively and omitting the unnecessary knowledge can significantly enhance the model performance to converge more quickly, which can be obtained by incorporating meta-learning techniques. To achieve satisfactory network performance using TL techniques, these must be designed carefully to avoid negative transfer.

5.2 Hybrid TL Technique

Incorporating TL with other machine learning techniques can be a good research problem. Because most existing ML techniques require enough training samples (which are not always possible because of the randomness and dynamicity of the UAV environment), TL enables to reuse training samples from similar environments which require further study.

5.3 Tradeoff between Training Time and Performance

In a model, minimizing the training time and ensuring the performance together are very complicated in most of the practical scenarios. In addition, in UAV environment, static and dynamic obstacles as well as wind disturbance bring several challenges in practical implementation [16]. Thus, tradeoff between the two issues should be effectively exploited in the design of TL algorithms in UAV networks.

6 CONCLUSIONS

In this paper, we have provided a comprehensive survey on TL algorithms in UAV networks. The background knowledge on TL has been given to allow the readers to gain a basic understanding of why TL is important in UAV networks. We have investigated six exiting TL algorithms in UAV networks with regard to design principles and operational characteristics, and compared them in terms of innovative features, advantages, and limitations. Finally, we have provided some open issues to motivate further research in this domain. We believe this work will be a reference to design effective TL techniques for UAV networks.

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