|| ISSN(online): 2589-8698 || ISSN(print): 2589-868X ||
International Journal of Medical and Biomedical Studies
Available Online at www.ijmbs.info
NLM (National Library of Medicine ID: 101738825)
Index Copernicus Value 2021: 70.61
Research Article
Volume 7, Issue 9; September: 2023; Page No. 01-07

Artificial Intelligence-Based Semantic Internet of Things

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Received: 09-06-2023 /Revised: 29-06-2023 /Accepted: 04-08-2023
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Conflict of interest: No conflict of interest.

Abstract

As more and more smart devices are connected to the internet, IOT technologies are enabling new uses in the SC that go beyond the SH. The people of a smart city (SC) may get the help they need thanks to SC technology. Connectivity between vast arrays of devices is made possible by IOT technology, making it a crucial enabler in a SC. Despite the fact that modeling the side-effects of sensing based on resource state is difficult and selecting the wrong actions could exacerbate the effect, AI-based Semantic Internet of Things (such as our Observer Effect MDP) approaches that take resource state into account will outperform those that do not.

Keywords: resource, Markov decision process, Internet of Things, Artificial Intelligence

Introduction

Many Internet-connected smart gadgets are already available on the market, and IOT technologies are enabling new uses in the SC that go beyond the SH. SCs comprise not just physical devices, but also certain virtual items (such as object qualities, data produced by devices, and human traits). Intelligent Medical Diagnosis (IMD), Intelligent Transportation System (ITS), Shopping Recommendation System (SRS), and so on are all examples of the kinds of situations that might be included in the SC. The SG can optimize the power supply, which in turn lowers overall energy usage, as will be explained. The ITS can calculate the most efficient travel path. On the other hand, the IMD is able to provide practical medical recommendations for the patient. At last, the SRS can provide informed product suggestions in response to consumer needs. The intelligent transmission and processing of a huge volume of data gathered from diverse devices/objects in the SC is the foundation of the common application scenarios in SC. Since QoE is becoming more vital in SC applications, intelligent services that aid users in making informed choices are growing in popularity. However, the need for intelligent services encourages the AI-enabled system in the SH because of the importance of data processing.

Traditional AI software is often tailored to a narrow set of use cases and objects and sometimes needs extensive user input to function properly. Therefore, it may be challenging to adapt traditional AI programs to a generic environment with several objects. However, standard AI systems are unlikely to be able to handle the wide variety of objects seen in SC. Therefore, it is necessary to advance artificial intelligence (AI) approaches for broad use. Different devices and functions, each with its own set of standards and protocols, allow these things to connect to the internet. Therefore, it is vital and required to build a platform that maps varied behaviors of objects to a consistent model, in order to guarantee that the AI effectively handles the SC service issues using IOT technology. In particular, the unified model allows for the merging of disparate items, which in turn makes AI processing easier. Semantic

technology, in particular, underpins the platform and unified model by characterizing object attributes for improved machine comprehension and enabling interoperability across many heterogeneous systems.

Literature Review

Guo, Kun & Lu (2018) the people of a smart city (SC) may get the help they need thanks to SC technology. Connectivity between vast arrays of devices is made possible by IOT technology, making it a crucial enabler in a SC. Interactional control issues arise, however, since these gadgets are often made by various companies using differing product standards. In addition, there will be a great need for intelligent service providers to effectively analyze the data produced by these devices. To facilitate the integration of diverse IOT devices in order to provide intelligent services, this study proposes a unique AI-based semantic IoT (AI-SIoT) hybrid service architecture. In particular, semantic and AI technologies fuel the proposed architecture and make it possible for diverse devices to link in a variety of ways. Artificial intelligence allows for more precise data analysis and swifter, more informed service provisioning choices. In addition, we describe a number of real-world applications of the proposed AI-SIoT architecture and explore the advantages and disadvantages of using it in future SCs.

Chander, Bhanu & Pal (2022) when it comes to the Internet of Things, artificial intelligence-based technologies are a must-have in the industry 5.0 paradigm. Industry 5.0 demonstrated a substantial link between intelligent systems and people via precise production automation with higher-order cognitive abilities in the majority of its use cases. Industry 5.0 also provides various capable tools that help businesses save money and adapt quickly with no up-front costs. There have been significant developments in the realms of smart devices, wireless communication, and sensor nodes in recent years, giving rise to IOT ecosystems. The Internet of Things (IOT) is a system of linked, Internet-enabled gadgets that may automatically collect and transfer data across a wireless network without any human intervention. The Internet of Things (IOT) has helped people feel less stressed and relieved. Users in even the most remote locations may now easily gather data for report writing thanks to IOT devices. They also advise humans properly with intelligent judgements using communication technology, as was indicated before. The raw sensed data collected by a plethora of interconnected devices is substantial and requires pre-processing. The necessary resources of IOT devices are what make edge computing really worthwhile, however. In order to infer information at the edge of the network, AI-based methods are required. In addition, the sensed data collected by IOT applications tend to be unstructured and need further analysis, which is where AI-based models come in.

Khan, Junaid & Khan (2022) many new digital technologies have their roots in the COVID-19 epidemic, which has served as an impetus for both reorientation and innovation. Even if global vaccination efforts continue to improve, eradicating this pandemic entirely would take a long time since new strains of the disease are always emerging. In order to prevent further spread of the pandemic, health care providers and caretaking organizations need access to cutting-edge technologies like the Internet of Things (IOT), Artificial Intelligence (AI), and Machine Learning, as well as advancements in these areas. IOT, AI, cloud computing, edge computing, deep learning methods, blockchain technologies, social networks, robotics, machines, privacy, and security are all discussed in this article, along with their present theoretical and practical possibilities. We analyzed the technologies included inside the overarching umbrella of AI-IOT technologies in the most condensed categorization system in light of these possibilities in conjunction with the COVID-19 pandemic. On this analysis, we showed how AI and IOT have had the greatest influence on the medical area. In terms of healthcare, the most important AI-IOT technologies discovered were fog computing in IOT, deep learning, and block chain. In addition, we used a unique approach combining methods from image processing, machine learning, and

differential system modeling to highlight numerous facets of these technologies and their potential effect.

Farheen, Mulla & Poorvika (2019). The notion of the internet of things (IOT) has become a cornerstone of the emerging technologies industry. Adding AI to IOT systems is the greatest option for handling the massive amounts of data that are generated and stored by these networks. Internet of Things data flows will include information sent and received from sensors and computers. There may be issues with storage, latency, channel restriction, and network congestion as a result of the rise in the number of workstations and sensors. Artificial intelligence, which is often conceived of in terms of data mining and network management and control, is able to get around this problem. The focus of this study is to demonstrate how AI may be used with IOT. This article uses the example of using artificial intelligence in autonomous vehicles to discuss the significance of data mining and management.

Huang, Yikun& Xue (2020) When Artificial Intelligence (AI) is combined with the Internet of Things (IOT), a communication and processing network of sensors is created. In order to address the heterogeneity issue between various sensors, sensor ontology must be used to annotate sensor data with the semantic meanings essential to establish communications and cooperations across intelligent systems on AIOT. The ideas, attributes characterizing a concept, and interactions between concepts are all explicitly modeled in AIOT sensor ontology. The ontology heterogeneity issue arises from the fact that human beings are subjective and hence a notion in multiple sensor ontologies may be defined with distinct terminologies and contexts. Because of this, ontology matching, also known as the integration of ontology information is required before these ontologies may be used. In this paper, we present a unique framework for matching sensor ontologies, one that combines three distinct Concept Similarity Measures (CSMs) with an alignment extraction strategy. Further, we present a compact Particle Swarm Optimization technique (cPSO) to optimize the aggregating weights for the CSMs and a threshold for filtering the alignment, therefore guaranteeing the alignments' quality. To evaluate cPSO, we use two sets of actual sensor ontologies and the conference track of the Ontology Alignment Evaluation Initiative (OAEI). The experimental findings demonstrate that cPSO's alignments are of statistically superior quality to those achieved using other top-tier sensor ontology matching methods.

Artificial Intelligence and Based Semantic Internet of Things

Here, we show off the outcomes of our AI experiments, to begin, we quickly confirm the presence of Bounded Rationality in this setting, where it manifests as diminished microscope precision. When assessing the former, we look at how well different methods of selecting sensing activities work. We next assess the latter by looking at how well each method does at its designated job and how closely sensing and performance is related. At last, we provide a quick conversation that sums up the takeaways from the AI research. Note that we examine learning algorithms that should improve over time, therefore our assessments of sensing and task performance look at both the overall outcomes and the results over time.

Bounded Rationality Validation

Before diving into the study of the findings, we quickly check that the state-dependent behavior of the microscope resource is reflected in the simulation outputs, demonstrating Bounded Rationality. This is crucial because 1) if the Bounded Rationality does not exist, then there is no reason to consider it within our solution approaches, and 2) if the Bounded Rationality does not exist, then we know for sure that the ability of the RL approaches to consider the Bounded Rationality is not the cause of their difference in performance (presented in the following sections). Remember that in the AI simulation, the Bounded Rationality manifests as less precise microscope readings owing to noise brought on by a less-than-ideal energy level in the microscope at the time of testing. In our studies, we use varying amounts of

noise to depict varying degrees of Bounded Rationality.

To prove the presence of Bounded Rationality in our AI studies, we show the average microscopy accuracy across all contexts and methods in Figure 1.1.

We find that the overall precision of the microscope tends to deteriorate across all methods as noise levels rise. Therefore, the Bounded Rationality is present in our trials.

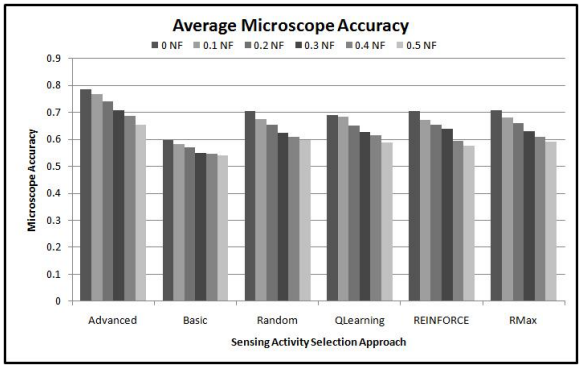

Figure 1.1: Average Microscope Accuracy for Artificial Intelligence

After showing that the experiments under consideration exhibit Bounded Rationality, we move on to analyzing the Artificial Intelligence results by comparing how different sensing activity selection strategies fared in terms of knowledge refinement on average. Figure 1.2 displays similar findings for all methods and settings. The two-way ANOVA findings in Table 1 reveal that these differences are significant (p 0.005).

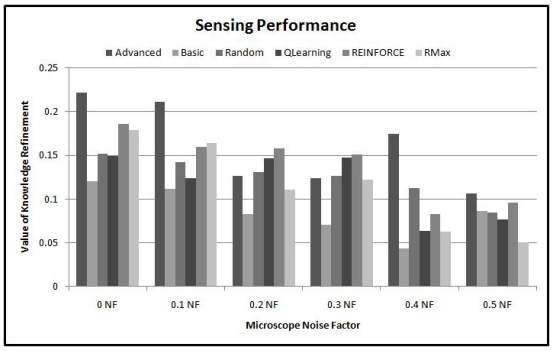

Figure 1.2: Sensing Performance in Artificial Intelligence

Table 1: Two-way ANOVA Results for Sensing Performance in Artificial Intelligence

Source of Variation	SS	df	MS	F	P-value	F crit
Environment	0.356758	5	0.071352	63.73987	4.14E-58	2.222674
Approach	0.51282	5	0.102564	91.6225	5.09E-80	2.222674
Interaction	0.032532	25	0.001301	1.162461	0.264806	1.516665
Within	1.168674	1044	0.001119			
Total	2.070784	1079				

We argue that there is not enough Bounded Rationality present at lower levels (i.e., 0 and 0.1 NF) to significantly skew sensing and hence make a difference in knowledge refinement.

Specifically, between 0 and 0.1 NF, the average value of knowledge refinement for the three straightforward methods yields very identical results. As a result, the negative impact of even a tiny quantity of Bounded Rationality (0.1 NF) is negligible compared to having no Bounded Rationality (0.0 NF) at all.

The sensing performance of methods that do not account for this impact degrades when the Bounded Rationality grows (i.e., at 0.2 and 0.3 NF). As a result, elevated levels of Bounded Rationality make it harder to hone one's expertise. However, RL-based systems may overcome this issue by learning the connection between the sensing state, the sensing actions, and the value of knowledge refinement to obtain very comparable sensing performance as when the Bounded Rationality is low.

All RL algorithms perform worse than in smaller NF amounts, following a similar trend to the non-RL approaches, suggesting that the Bounded Rationality increases to a point where considering its effect on knowledge refinement is not enough to counter this challenge. Although its general performance degrades with increasing OE, we do find that the Advanced method does very well at the 0.4 NF level of Bounded Rationality. However, we consider this to be an exception since it drops again at 0.5 NF, showing a clear downward trend in sensing performance.

These findings lead us to the conclusion that taking into account the status of available resources and the Bounded Rationality may boost sensing performance, albeit we should stress that this is only true for moderate to high degrees of Bounded Rationality. To better foresee when this problem will arise, we want to study the context of its emergence, and we will also look into methods to modify our approach to deal with cases of Bounded Rationality.

We next examine the temporal sensing performance of each method. Each experiment is divided into smaller time intervals (termed Task Groups) depending on the order in which the agents complete their tasks, with the deadline for the fifth4th task in a Task Group serving as the breakpoint for each period. Because we utilize reinforcement learning methods to solve the Bounded Rationality HMM, a time series analysis of the findings is crucial; in general, in artificial intelligence research, we hope that a learning technique will become better as time goes on.

In Figure 1.3 we show the results of sensing performance with time in the 0.3 NF environment. Two major inferences about the other settings' Bounded Rationality can be drawn from this diagram:

None of the methods performs noticeably better than the others across the board. Overall findings are statistically significant, but it does not mean one method is sure to perform better than the others at any particular moment.

Moreover, not even the RL methods show steady performance improvements over time. There are few settings (0.4 and 0.5 NF) where the Bounded Rationality becomes too challenging to manage, but overall, the RL techniques outperform the Random approach over time. for the 0.3 NF and 0.5 NF settings, we illustrate this pattern and its exception. Because RL techniques begin with equal rewards for all actions in all states (or near equal random values in the case of REINFORCE's neural networks), without learning, they deteriorate into Random. That reinforcement learning helps the agent's sensing performance may be shown by comparing the RL techniques' results to those of Random.

Similarly, in the 0.2 NF environment shown in Figure 1.7, we see that, in general, the RL techniques improve with time compared to Random up until the very final task group. We think this is an outlier because the Random technique does less sensing in the final task group, leading to less knowledge refinement and hence a lower average value being computed.

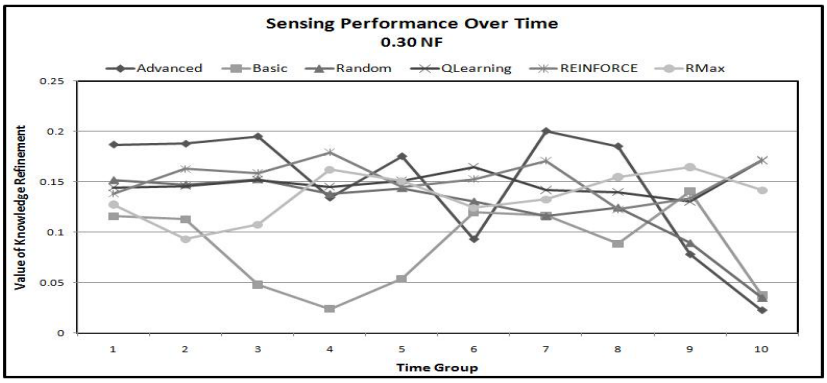

Figure 1.4: Sensing Performance over Time in Artificial Intelligence (0.3)

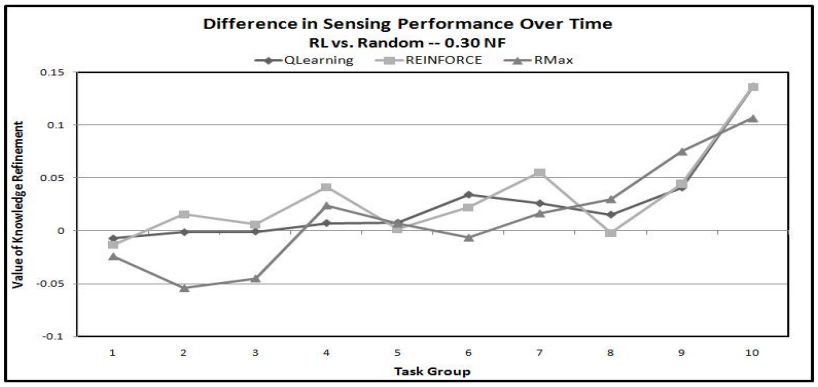

Figure 1.5: Sensing Performance of RL vs. Random over Time in Artificial Intelligence (0.3)

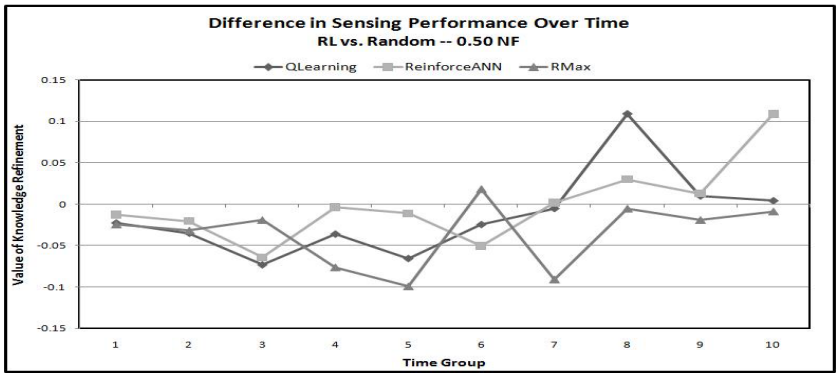

Figure 1.6: Sensing Performance of RL vs. Random over Time in Artificial Intelligence (0.5)

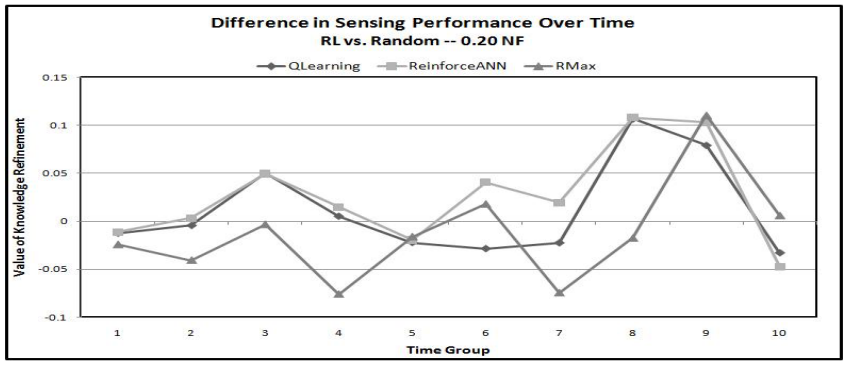

Figure 1.7: Sensing Performance of RL vs. Random over Time in Artificial Intelligence (0.2)

Conclusion

We analyze how well different methods of sensing perform over time. Each experiment is divided into smaller time intervals (termed Task Groups) depending on the order in which the agents complete their tasks, with the deadline for the fifth4th task in a Task Group serving as the breakpoint for each period. Since we utilize reinforcement learning techniques to solve the Bounded Rationality HMM, analyzing the outcomes over time is crucial. In the field of artificial intelligence, it is often desired that learning methods gradually become more effective.

Reference

1. Huang, Yikun& Xue, Xingsi& Jiang, Chao. (2020). Semantic Integration of Sensor Knowledge on Artificial Internet of Things. Wireless Communications and Mobile Computing. 2020. 1-8. 10.1155/2020/8815001.
2. Farheen, Mulla & Poorvika, Naaz & Prasanna, P & Mohammad, Sameer. (2019). Application of artificial intelligence on internet of things (IOT). SSRN Electronic Journal. 6. 510-514.
3. Khan, Junaid & Khan, Jebran & Ali, Furqan & Ullah, Farman & Bacha, Jamshid & Lee, Sungchang. (2022). Artificial Intelligence and Internet of Things (AI-IOT) Technologies in Response to COVID-19 Pandemic: A Systematic Review. IEEE Access. 10. 10.1109/ACCESS.2022.3181605.
4. Chander, Bhanu & Pal, Souvik & De, Debashis&Buyya, Rajkumar. (2022). Artificial Intelligence-based Internet of Things for Industry 5.0. 10.1007/978-3-030-87059-1_1.
5. Guo, Kun & Lu, Yueming& Gao, Hui & Cao, Ruohan. (2018). Artificial Intelligence-Based Semantic Internet of Things in a User-Centric Smart City. Sensors. 18. 1341. 10.3390/s18051341.
6. Alvear, O.; Calafate, C.T.; Cano, J.C.; Manzoni, P. Crowdsensing in Smart Cities: Overview, Platforms, and Environment Sensing Issues. Sensors 2018, 18, 460.
7. Viani, F.; Robol, F.; Polo, A.; Rocca, P.; Oliveri, G.; Massa, A. Wireless architectures for heterogeneous sensing in smart home applications: Concepts and real implementation. Proc. IEEE 2013, 101, 2381–2396.
8. Bisio, I.; Lavagetto, F.; Marchese, M.; Sciarrone, A. Smartphone-centric ambient assisted living platform for patients suffering from co-morbidities monitoring. IEEE Commun. Mag. 2015, 53, 34–41.
9. Corno, F.; Razzak, F. Intelligent energy optimization for user intelligible goals in smart home environments. IEEE Trans. Smart Grid 2012, 3, 2128–2135.
10. Chen, L.; Nugent, C.; Okeyo, G. An ontology-based hybrid approach to activity modeling for smart homes. IEEE Trans. Hum. Mach. Syst. 2014, 44, 92–105.