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Adaptive Linear Neuron (ADALINE) with Edge Computing for Reliable Data Computation

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Abstract

Edge computing is used to minimize the data transfer rate from the various sensor to the main computing node by filtering the unwanted information from the raw data. In such situations Edge Computing devices will face challenges like network speed, distributed computing, delay, security, data accumulation. Here we going to address the few solutions for improving the data accuracy and to provide reliable data to the main computing node. We propose a model for reliable data collection using Adaptive Linear Neuron with Edge Computing, in which we having two segments such as Reliable data collection and irregularity data detection approach. We use multiple view sensor data collection to generate a reliable data and applying machine learning reinforcement learning to identify the irregular data from the sensors. Our implementation improves the performance in the aspects of IoT devices energy consumptions and provides reliable information to the computing system.

Keywords*: Adaptive Linear Neuron, Anomaly Detection, Edge Computing, Internet of Thing, Multi-dimensional, Reinforcement Learning*

1. Introduction

Internet of Things (IoT) technology uses various sensors to get the availability, position, characteristics and appearance of an object. Since, most of the IoT devices are using Machine to Machine communication, it keeps on generating the raw data for 24/7 daily. So, this will lead to challenges like network bandwidth, data computing, data analyzing, security, distributed computing and storing the data[3]. Even though we had cloud storage it's very difficult to process the large amount of data, for that we are using Edge Computing. It brings the flexibility of storing the useful data in cloud store before its transmitted over the network.

The Edge Computing used to process the data over the edges of connected network. Edge Computing has the feature like less energy consumable, location aware devices, flexible mobility support, reduce latency [4].The Edge computing will reduce the data transfer rate by removing the unwanted data available in the raw data. It performs the basic computing operations on the edges of the networks. The challenges like scalability enhancements, security and privacy, self-organization, functional integration and resource management are likely to be accorded in Edge Computing process [5].

To solve few problems in the edge computing, we are using Adaptive Linear Neuron (ADALINE) which is actually a Neural Network based. It's been used for pattern findings, effective prediction, classical classification and regression analysis. The neural network computing time is depending on the parameters like given inputs, weights, learning rate, activation function and architecture[6]. The ADALINE is a single layer artificial neural network, since edge computing works in a light weight manner. Input to the Adaline is processed by the following two sub process to generate a reliable data for computation,

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(i) Multidimensional Sensing:
Enables the devices to sense properties and characteristics could increase the accuracy of monitoring and provides reliable information to the computing nodes[7].
(ii) Reinforcement Learning:
This will improve the multiple learning and data correctness in the sensing environment[8].

2. Literature Survey

The authors in this paper [1]collected trustworthy data by implementing multiple sensor to get the multidimensions of a particular thing to ensure the trusted values to their computing. We can also use two-layer recognition as stated [9], first layer by coarsely classifier and second layer by neural network with Hidden Markov Model (HMM). But in our problem statement of edge computing, it’s very difficult to use two layers since it’s a light weight device. The deployment issues of heterogenous wireless sensor network can be used using 3D data, in which multi-objective optimization problem can be rectified and gives assurance for connectivity and reliable data delivery [10]. When sensors receive multiple commands simultaneously the coupling resource problem will occur, this issue is tackled by using Hungarian algorithm as proposed in the paper [11]. So, that our sensors can constructs a queue and process all the request in the FIFO order without losing any tasks. The wrong information generated by sensors will intent to make wrong decisions, to overcome such abnormal behavior of sensor, the author [12] address by using Fog-Based Detection System (FDS).

Whenever we dealing with large number of sensors and nodes, it will cause traffic in the network due to the bottle neck problem. This bottle neck can be solved by having multiple mobile sinks and each sink is controlled by a sensor. So, that sensors can receive multi-input and pass forward multi-output to lead the future development of the systems [13].The transmit the data long distance from the edge computing device to main computing system, we relay-nodes. Data must choose an optimal relay-node to reach the destination node by using shortest path, for that write implemented black-burst-assisted mechanism [14]. The performance of the relay-nodes is measured by latency and packet delivery ratio. More over the accuracy of data generated by sensors are analyzed and trusted by using the parameters like devices, persons and timeline [15]. Collaborative Multi-Tasks Data Collection Scheme (CMDSC) is suggested by the writer [16], it will perform the highest ratio of task to the amount of data and greedy involved density reduce the cost of data collection and increases the systems profits. Along with the reliable data, the reputation of the nodes also important, this can be done by trust value for each node which performed robust during large number of anonymous nodes that provides fake values [17].

The anomaly detection can be solved by using contextual bandit which uses single layer Markov decision easily [2]. This improves high adaptive anomaly detection in the hierarchical edge computing network (HEC). When we do this many process in edge computing, we need to think of latency consideration. The latency concern is addressed by the author as using multi-algorithm approach that reduce in delay between the nodes from its end points [18]. Regarding with the data compression, the stage process like pruning the data, trained quantized to find the pattern of data and Huffman coding to compress the data. This will improve significant improvement in the usage of storage, network bandwidth and computation process [19]. Edge computing devices are mostly run with battery power, the high complex computing will consume more power. To overcome such condition, we can also opt to compute the data in cloud data center itself. As stated by the author by using Deep Neural Network (DNN) in the cloud, improved the latency, energy requirement and less overhead on Edge Computing devices [20].

Based on the time stamping of generated data, the anomaly can be identified as proven by the author, they used time series dicords by having certain within time limit [21].By using human-driven and device-driven machine learning intelligence, we can improve the delay requirement in certain time critical devices and energy consumption is stated with two case studies by the authors [22]. Anomalies also cause due to malfunctionof sensors, damages caused by the natural climates to the Wireless Sensor Networks (WSN). By using two-level algorithm, one monitors the sensors and the other monitors the IoT enabled cloud platforms. The synchronized data of sensors and IoT Cloud is used to identify the anomaly [23].

In most of the Reinforcement Learning (RL) uses the ordinary function approximations, Richard S. Sutton author of the paper given a method which uses its own functional approximation, which deals the function value as a sole property. With this idea the function approximation can be converged in a local optimal manner [24]. The weight of the function approximation can be adjusted to get our required target output by using gradient of expected reinforcement [25]. Data collection from various sensors implemented in the distributed environment and connected a hierarchical wireless network can be accomplished by Distributed Deep Neural Networks (DDNN), the advantage had by the implemented authors are minimize usage of resources and communications between the devices, maximize the productivity in the cloud platform for Edge Computing [26]. Choosing the reliable data from the multidimension sensor is the tedious process and need to give more importance to it. Because based on the trusted data the expected computational outputs produce the quality. So, the dynamic learning and choosing of trusted sensor data using BlockDrop approach stated by the authors [27].

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3. Problem Considerations and Construction of Model

In the Internet of Things most of the sensors are connected two ways, namely Hierarchical Model and Linear Model. In both the models, there are x sensors and controlled by y base nodes. The number of base nodes is depts on the deployment model used in the IoT. In traditional IoT deployment approaches, single sensors are used to detect the environment situation. Based on the data sent by the sensors, the edge computing will perform corresponding operations. When the primary sensor does malfunction or failed to work due to some natural calamities, there is other option to process in the particular faulty node location. So, to avoid such kinds of situation, we suggest Adaptive Linear Neuron (ADALINE) with Reinforcement Learning (RL) which has the following major processes.

(i) Multi-dimensional sensing data for reliable data collection

In the existing model's sensor nodes are measure as a single attribute, which maybe lead to biases depends on particular node performance. As shown in Figure 1 multiple sensors are used to detect the status of the objects, this forms a multi-dimensional data for accurate predict and produces a reliable data for computing. All the sensors are linked with Edge computing node, the trusted data will be shared for cloud computing process. This multiple sensor can be made as clusters and the sensors adjacent exchange information's between them.

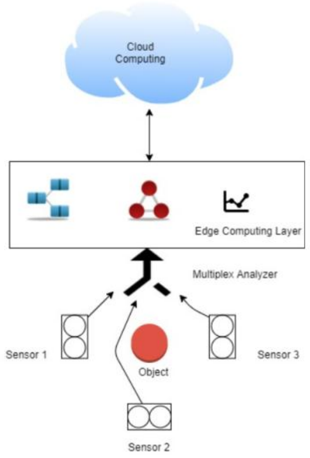

Figure 1: Multi-dimensional data collection for accuracy

In aspect of reducing the power consumption, base nodes can able to choose shortest distance sensor. The trusted primary sensor fails to generate the data, the base node will consider the neighboring sensor values. The cluster can able to do the energy balance between the cluster sensors, which will lead to long run of the operation.

The y base node identifies the trusted node from the x number of sensors by using the trust value used for each and every connected sensor in the cluster. The trust value is calculated by starting the directly connected sensors with the y base node, if the sensors are not directly connected it is accounted as N + distance from base node y (multi-hop). Thus, according to the trust value of sensors the base node considers the shortest value as trusted data.

(ii) Reinforcement Learning for anomaly detection

In the second stage of the Edge Computing, mostly concentrate on reliable data delivery to the cloud from the sensors. Which reduces the processing power, increase the life time of energy, and miscommunication between the sensors and nodes. By using Reinforcement Learning the single layer neural network can detect the input data generated by the sensors. The RL automatically learning capability by adjusting the weightage assigned by the model.

As shown in the Figure 2 Adaptive Linear Neuron (ADALINE) is implement by using Reinforcement Learning, the sensors S1, S2,…Sn and weightage W1, W2,…Wn given to input function which produce the product of sensor data and weightage as output. The RL observes the activation function and check for qualified target value. The process will be repeated until it reaches the sustainable desired output, which will be accurate and the anomaly data removed in Edge Computing node itself.

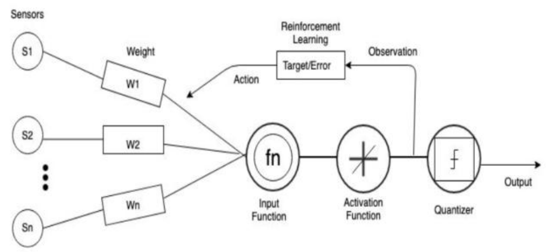

Figure 2: Reinforcement Learning in Adaptive Linear Neuron

The RL keep on observe the output of the activation function, and gives the suggestions to take corrective action. Hence the abrupt data and missing of data can be easily identified in the sensing level itself, this will improve the convergence rate.

4. Experiment and Performance Evaluation

The practical implementation of Adaptive Linear Neuron (ADALINE) with Edge Computing for Reliable Data Computation test in Tensorflow, the Linux traffic control tool is used to measure the latency, bandwidth transferred between nodes. The complete simulation model is performed at IoT devices, edge nodes, and cloud computing setup along with Tensorflow. Randomly deployed 5 sensors and formed as a cluster with a base node. The sensors are in the bottom layer, controlled by Edge Computing

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base node over that Cloud service providers are placed similar to the Figure 1. The transmission time taken to reach edge layer to cloud layer is 12 ms with the data transfer rate at 10^6 bit/s. We build an Adaptive Neural Network which has single layer neural network with 50 units and 1output layer, the Reinforcement Learning is trained with the network policy based on the working environment to increase the accuracy.

The evaluation of our proposed model deals with accuracy of the collected data and to identify the misleading sensor nodes. In Figure 3 shows that accuracy is above 99 %, since we deployed multi-dimensional sensor for focus on particular object. The Reinforcement Leaning is trained by network policy, it observing the output of activation function the relevant weight (Wn) is adjusted. For the weight (Wn) of 0.004 it produces the accuracy rate to 99.5%. Comparing the delay performance with the accuracy and weight, its shown that delay is increasing depends on the increase in accuracy and weight. So, the accuracy is 99% the delay is 4 ms, the accuracy reaches 99.5% the delay reached to 10 msdue to increase in weight till 0.005.

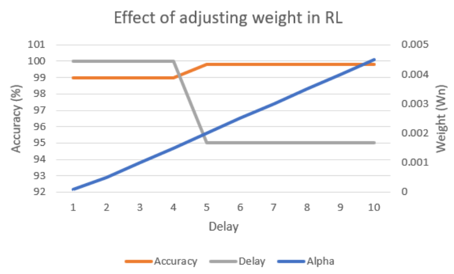

Figure 3: Evaluation of Accuracy, Delay and Weight using ADALINE-RL

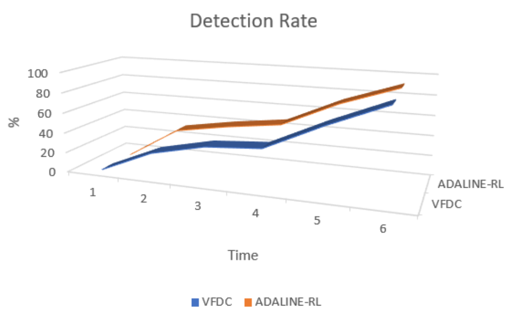

Figure 4: Anomaly detection rate between VFDC and ADALINE-RL

The anomaly or misleading sensors detection rate is compared with Virtual Force mapped by trusted value (VFDC) and ADALINE-RL. As shown in the output graph the detection of anomaly takes much time, when the detection rate is 80% the nominal time takes to identify it is around 6 ms. When compared with the existing VFDC our proposed ADALINE-RL detects anomaly with higher rate.

5. Conclusion

The advancement in Edge Computing provides new enhancement in Internet of Things research domain. The base for all the operation is source of inputs given to the computing. In order to improve the reliable input data generation in the lack of computing environment, we proposed and implemented a model Adaptive Neural Network with Edge Computing for Reliable Data Generation by using Reinforcement Learning. Result of it the trusted sensors are easily identified dynamically and our system is not relying on single sensor. Using Reinforcement Learning the system can get the feedback of Activation Function by observing, based on that the correction modification are made to get the reliable quantified computing process in the cloud computing. Our experiment result shows the best performance in the aspect of accuracy, and anomaly detection. For the future enhancement can consider to improve the energy efficiency improvement in the multiple sensing environment.

References

[1] T. Wang, L. Qiu, A. K. Sangaiah, A. Liu, M. Z. A. Bhuiyan, and Y. Ma, "Edge Computing based Trustworthy Data Collection Model in the Internet of Things," IEEE Internet Things J., vol. XX, no. XX, pp. 1–1, 2020.

[2] M. V. Ngo, H. Chaouchi, T. Luo, and T. Q. S. Quek, "Adaptive Anomaly Detection for IoT Data in Hierarchical Edge Computing," 2020.

H. Fu, G. Manogaran, K. Wu, M. Cao, S. Jiang, and A. Yang, "Intelligent decision-making of online shopping behavior based on internet of things," Int. J. Inf. Manage., vol. 50, no. November 2018, pp. 515–525, 2020.

[3] W. Z. Khan, E. Ahmed, S. Hakak, I. Yaqoob, and A. Ahmed, "Edge computing: A survey," Futur. Gener. Comput. Syst., vol. 97, pp. 219–235, 2019.

[4] R. Yang, F. R. Yu, P. Si, Z. Yang, and Y. Zhang, "Integrated Blockchain and Edge Computing Systems: A Survey, Some Research Issues and Challenges," IEEE Commun. Surv. Tutorials, vol. 21, no. 2, pp. 1508–1532, 2019.

[5] R. Rathinasabapathy and M. Ravindran, "Design and analysis of adaptive artificial learning architecture to model non-linear systems using different activation functions," Int. J. Appl. Eng. Res., vol. 14, no. 6, pp. 1305–1312, 2019.

S. Qian, S. Sun, Y. Wang, Z. Li, and H. Lin, "Recent advances of multidimensional sensing: from design to applications," Sci. China Chem., vol. 62, no. 12, pp. 1601–1618, 2019.

May - June 2020
ISSN: 0193-4120 Page No. 3263-3267

[6] M. Jaderberg et al., "based reinforcement learning," vol. 865, no. May, pp. 859–865, 2019.

[7] J. Qi, P. Yang, M. Hanneghan, S. Tang, and B. Zhou, "A hybrid hierarchical framework for gym physical activity recognition and measurement using wearable sensors," IEEE Internet Things J., vol. 6, no. 2, pp. 1384–1393, 2019.

[8] B. Cao, J. Zhao, P. Yang, P. Yang, X. Liu, and Y. Zhang, "3-D Deployment Optimization for Heterogeneous Wireless Directional Sensor Networks on Smart City," IEEE Trans. Ind. Informatics, vol. 15, no. 3, pp. 1798–1808, 2019.

[9] T. Wang, Y. Liang, W. Jia, M. Arif, A. Liu, and M. Xie, "Coupling resource management based on fog computing in smart city systems," J. Netw. Comput. Appl., vol. 135, no. March, pp. 11–19, 2019.

[10] G. Zhang, T. Wang, G. Wang, A. Liu, and W. Jia, "Detection of hidden data attacks combined fog computing and trust evaluation method in sensor-cloud system," Concurr. Comput. , no. March, pp. 1–13, 2018.

[11] T. Wang et al., "Data collection from WSNs to the cloud based on mobile Fog elements," Futur. Gener. Comput. Syst., vol. 105, pp. 864–872, 2020.

[12] D. Cao, B. Zheng, B. Ji, Z. Lei, and C. Feng, "A robust distance-based relay selection for message dissemination in vehicular network," Wirel. Networks, vol. 26, no. 3, pp. 1755–1771, 2020.

[13] J. Qi, P. Yang, L. Newcombe, X. Peng, Y. Yang, and Z. Zhao, "An overview of data fusion techniques for Internet of Things enabled physical activity recognition and measure," Inf. Fusion, vol. 55, no. July 2019, pp. 269–280, 2020.

[14] Y. Ren, W. Liu, T. Wang, X. Li, N. N. Xiong, and A. Liu, "A Collaboration Platform for Effective Task and Data Reporter Selection in Crowdsourcing Network," IEEE Access, vol. 7, no. 2, pp. 19238–19257, 2019.

[15] X. Chu, X. Chen, K. Zhao, and J. Liu, "Reputation and trust management in heterogeneous peer-to-peer networks," Telecommun. Syst., vol. 44, no. 3–4, pp. 191–203, 2010.

[16] Z. Chen et al., "An empirical study of latency in an emerging class of edge computing applications for wearable cognitive assistance," 2017 2nd ACM/IEEE Symp. Edge Comput. SEC 2017, 2017.

[17] S. Han, H. Mao, and W. J. Dally, "Deep compression: Compressing deep neural networks with pruning, trained quantization and Huffman coding," 4th Int. Conf. Learn. Represent. ICLR 2016 - Conf. Track Proc., pp. 1–14, 2016.

[18] Y. Kang et al., "Neurosurgeon: Collaborative intelligence between the cloud and mobile edge," Int. Conf. Archit. Support Program. Lang. Oper. Syst. - ASPLOS, vol. Part F1271, pp. 615–629, 2017.

[19] E. Keogh, J. Lin, and A. Fu, "HOT SAX Finding the Most Unusual Time Series Subsequence: Algorithms and Applications," Icdm, p. 8, 2005.

[20] Q. D. La, M. V. Ngo, T. Q. Dinh, T. Q. S. Quek, and H. Shin, "Enabling intelligence in fog computing to achieve energy and latency reduction," Digit. Commun. Networks, vol. 5, no. 1, pp. 3–9, 2019.

[21] T. Luo and S. G. Nagarajany, "Distributed anomaly detection using autoencoder neural networks in WSN for IoT," IEEE Int. Conf. Commun., vol. 2018-May, 2018.

[22] M. Paczkowski, "Low-friction composite creping blades improve tissue properties," Pulp Pap., vol. 70, no. 9, 1996.

[23] R. J. Willia, "Simple Statistical Gradient-Following Algorithms for Connectionist Reinforcement Learning," Mach. Learn., vol. 8, no. 3, pp. 229–256, 1992.

[24] S. Teerapittayanon, B. McDanel, and H. T. Kung, "Distributed Deep Neural Networks over the Cloud, the Edge and End Devices," Proc. - Int. Conf. Distrib. Comput. Syst., pp. 328–339, 2017.

[25] Z. Wu et al., "BlockDrop: Dynamic Inference Paths in Residual Networks," Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit., pp. 8817–8826, 2018.