This is an Accepted Manuscript of an article published by Taylor & Francis in **CYBERNETICS AND SYSTEMS** on 20.01.2020, available online: https://www.tandfonline.com/doi/full/10.1080/01969722.2019.1705545

Postprint of: Zhang H., Li F., Wang J., Wang Z., Shi L., Sanin C., Szczerbicki E.: The Neural Knowledge DNA Based Smart Internet of Things CYBERNETICS AND SYSTEMS Vol. 51, iss. 2 (2020), pp.258-264

The Neural Knowledge DNA based Smart Internet of Things

Haoxi Zhang [a], Fei Li [a], Juan Wang [a], Zuli Wang [a], Lei Shi [a], Cesar Sanin [b], Edward Szczerbicki [c]

[a] School of Cybersecurity, Chengdu University of Information Technology, Chengdu, China; [b] School of Mechanical Engineering, The University of Newcastle, Newcastle, NSW, Australia; [c] Faculty of Management and Economics, Gdansk University of Technology, Gdansk, Poland

Abstract. The Internet of Things (IoT) has gained significant attention from industry as well as academia during the past decade. Smartness, however, remains a substantial challenge for IoT applications. Recent advances in networked sensor technologies, computing, and machine learning have made it possible for building new smart IoT applications. In this paper, we propose a novel approach: the Neural Knowledge DNA based Smart Internet of Things that enables IoT to extract knowledge from past experiences, as well as to store, evolve, share, and reuse such knowledge aiming for smart functions. By catching decision events, this approach helps IoT gather its own daily operation experiences, and it uses such experiences for knowledge discovery with the support of machine learning technologies. An initial case study is presented at the end of this paper to demonstrate how this approach can help IoT applications become smart: the proposed approach is applied to fitness wristbands to enable human action recognition.

Keywords: knowledge representation; intelligent system; smart Internet of Things; Set of Experience Knowledge Structure; deep learning.

Address correspondence to Haoxi Zhang, Chengdu University of Information Technology, No. 24 Block 1, Xuefu Road, Chengdu, China. E-mail: haoxi@cuit.edu.cn

INTRODUCTION

Extracting valuable information from data produced by Internet of Things (IoT), and transforming this information into knowledge to empower IoT to become intelligent is the most challenging part and the essential goal of the concept of IoT (Gubbi et al. 2013; Lin et al. 2017). By utilizing artificial intelligence technologies, such as data mining and machine learning, smartness and intelligence can be added to IoT (Tsai et al. 2014; Siryani et al. 2017).

Several IoT smart enhancement proposals and techniques for a number of different domains can be found in literature. Siddiqui et al. (2018) proposed a knowledge-based analytics to observe abnormal variations among stored data and to present a work-flow to balance the data load among healthy and unhealthy IoT devices in a smart grid. In another work, Lokshina and Lanting (2019) try to give a reasonable, qualitative evaluation of IoT-driven eHealth from theoretical and practical viewpoints. They look at associated knowledge management issues and contributions of IoT to eHealth, along with requirements, benefits, limitations, and entry barriers. Burton et al. (2018) introduced a disposable IoT gardening soil sheet, capable of analyzing real–time soil nitrate concentration during leaching and irrigation events. Siryani et al. (2017) introduced a framework for a decision-support system that operates within the IoT ecosystem. The system controls advanced analytics of electric smart meter (ESM) network communication data to improve cost predictions for field operations. It provides actionable decision recommendations regarding whether to send a technician to a customer location to resolve an ESM issue. The system is empirically evaluated using data sets from a commercial network, and the results demonstrate that this approach generates statistically noteworthy estimations and that the system actually improves the cost efficiency of ESM network operations and maintenance. Al-Ali et al. (2018) presented an energy management system for smart homes. In their system, each home device is interfaced with a data acquisition module that is an IoT object with a unique Internet Protocol (IP). The data acquisition system on chip module collects energy consumption data from each device of each smart home and transmits the data to a centralized server for further processing and analysis.

According to the most current surveys and studies (Wu et. Al 2017; Siow et al. 2018; Mohammadi & Al-Fuqaha 2018), and after a comprehensive comparison of different data mining and machine learning technologies, as well as their applications for IoT, it can be seen that by using artificial intelligence technologies the IoT can be enhanced with smartness and intelligence. This paper presents a novel approach, the Neural Knowledge based Smart Internet of Things concept, that enables IoT to extract knowledge from its experiences, as well as store, evolve, share, and reuse such knowledge aiming for intelligent functions.

NEURAL KNOWLEDGE DNA (NK-DNA) CONCEPT

Experience is gained through the practice of daily decision making processes (Sharma et al. 2012). Experiential knowledge combines decision tasks with results allowing for intelligent cognition, and can be regarded as perfect resource in the course of adding smartness to the IoT. However, knowledge is useful only if it is accessible in the process of problem solving and decision making. To create this accessibility, the Neural Knowledge DNA (NK-DNA) was proposed in Zhang et al. 2016. NK-DNA is designed to extract, store, evolve, share, and reuse knowledge for intelligent systems. It uses artificial neural networks as the central capacity which provides its smartness. It applies the ideas of deep learning technology to the scope of knowledge representation (Lecun et al. 2015).

The NK-DNA consists of four essential elements: States, Actions, Experiences, and Networks (Figure 1).

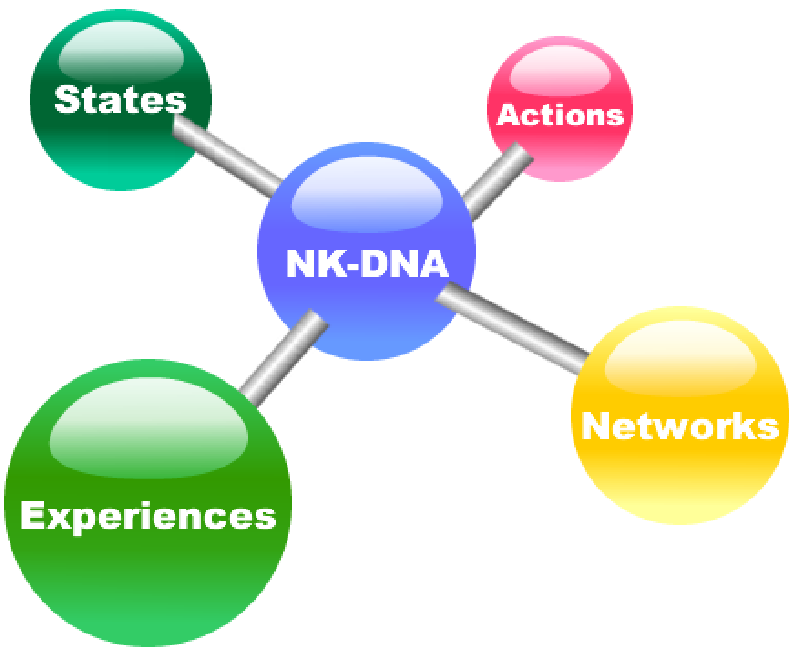

Figure 1. Conceptual structure of the NK-DNA

The structure in Figure 1 can be briefly characterized as follows:

1. States are situations in which a decision or a motion can be made or performed,

2. Actions are used to store the decisions or motions the domain can select,

3. Experiences are domain's historical operation segments with feedbacks from outcomes, and

4. Networks store the detail of neural networks for training and using such knowledge, like network structure, connections, weights, bias, and deep learning framework used.

The NK-DNA's four-element combination is designed to carry detailed information about decisions and their outcomes. States are situations in which a decision or a motion can be made or performed. Actions store decisions or motions available for selection in a given domain. Experiences are domain's historical operation segments with feedback from decision making outcomes. And Networks store the description of neural networks which are used for training purposes, such as the network structure, weights, bias, and deep learning framework used.

Knowledge in the NK-DNA system is captured as models structured after training in deep learning procedures. These model store detailed information about weights and biases of connections between neurons of the neural network used for training, and the hierarchy of this network. Another important feature of this approach is that the

NK-DNA uses previous decisional experience as the main source to collect and expand intelligence for future decision making. Experience in the NK-DNA is stored as the Set of Experience Knowledge Structure (SOEKS) (Sanin et al. 2018). As the system transitions from one state to another during its operation, and makes decisions (performs actions) in each state, it receives feedback from its progression. Integrated information of these states, actions, feedbacks, and transitions makes up the NK-DNA experience.

INITIAL CASE STUDY

Normally, IoT applications are constantly executing myriads of decisions which constitute their decisional experience. In most cases, such experience is not used to assist and enhance future decisional events, is not shared, and is disregarded. In our approach we propose to use the decisional experience as the main source of knowledge and smartness. For initial illustration purposes, our approach is applied to fitness wristbands for activity classification. We developed a smart phone application that reads the wristband's three-axis accelerometer through Bluetooth to collect data and sent collected data to our server for further processing (i.e. for activity classification).

The most important factor attributed to the success of the activity classification is to find a proper representation of the absorbed data. The data collected through the fitness wristbands are time series data that carry the three-axis accelerometer readings linked with different activities. Figure 2 illustrates a sample of such data.

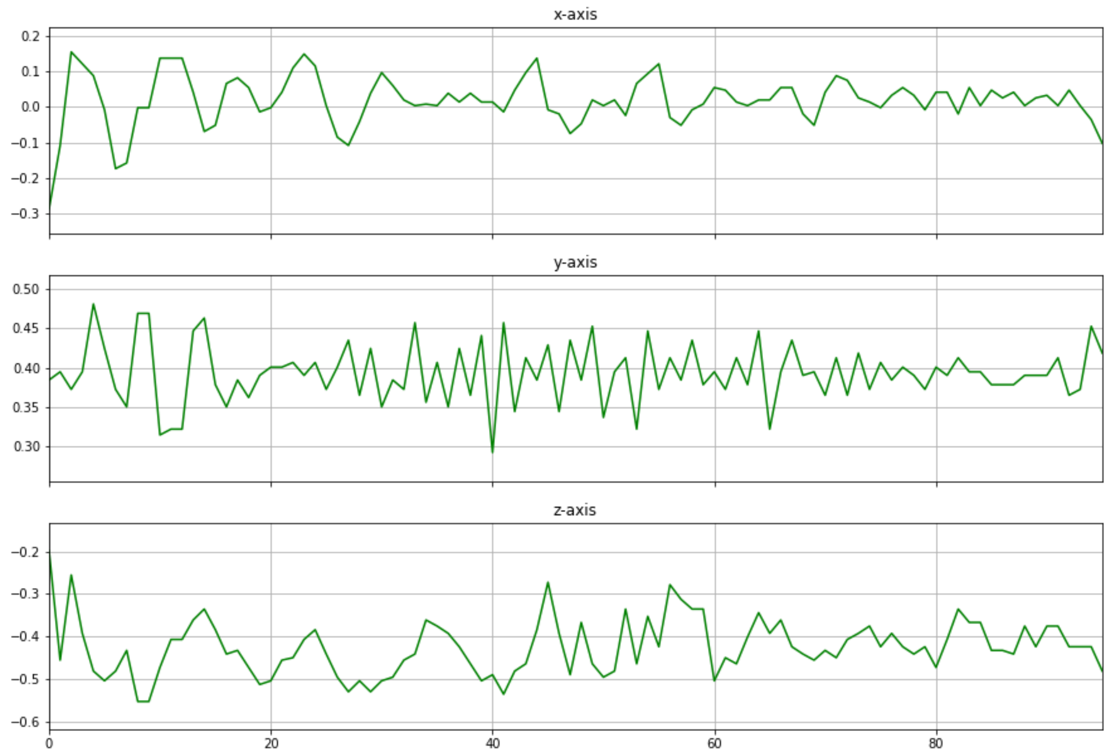

Figure 2. A sample segment of time series from the accelerometer data.

Our proposed NK-DNA utilizes deep learning for feature extraction and classification. In this case study, the convolutional neural networks (CNN) are applied to tackle time series data. The CNN is conducting different processing units (e.g. convolution, pooling, sigmoid/hyperbolic tangent squashing, rectifier and normalization) alternatively. Such a variety of processing units can automatically learn a unique set of optimized features of the signals (Lecun et al. 2015). A sliding window is adopted to segment the time series signal into a collection of short pieces of signals. Specifically, an instance used by the CNN is a two-dimensional matrix containing *m* raw samples (each sample with N attributes). Here, *m* is chosen to be 96, which carries about 3 seconds of continuous readings. In addition, the label of each 96-step segment is determined by the most-frequently happened label for that 96-step raw record.

In the convolution layers, the previous layer's feature maps are convolved with several convolutional kernels. The output of the convolution operators added by a bias is put through the activation function to form the feature map for the next layer. For the j^{th} feature map in the i^{th} layer of the CNN, it is also a matrix, and the value at the x^{th} row is denoted as v_{ij}^{x}. Formally, the value v_{ij}^{x} is given by

$$v_{ij}^{x} = \tanh\left(b_{ij} + \sum_m \sum_{p=0}^{P_i-1} w_{ijm}^{P} v_{(i-1)m}^{x+P}\right), \tag{1}$$

where $\tanh(\cdot)$ is the hyperbolic tangent function, b_{ij} is the bias for this feature map, w_{ijm}^{p} is the value at the position p of the convolutional kernel, *m* indexes over the set of feature maps in the $(i-1)^{th}$ layer connected to the current feature map, and P_i is the length of the convolutional kernel. In the pooling layers, the resolution of feature maps is reduced to increase the invariance of features to distortions on the inputs. More specifically, feature maps of the previous layer are pooled by the maxpooling function

$$v_{ij}^{x} = \max_{1 \le q \le Q_i}(v_{(i-1)j}^{x+q}). \tag{2}$$

Based on the above introduced operators, we construct a 7-layer CNN to learn different activity features. After training, the proposed approach achieved 92% accuracy on the test dataset.

CONCLUSIONS AND FUTURE WORK

In this paper, we introduced a novel approach: the Neural Knowledge DNA based Smart Internet of Things that enables IoT to extract knowledge from their past experiences, as well as storing, evolving, sharing, and reusing such knowledge aiming for smart functions. We applied this proposed approach to fitness wristbands to enable the wristbands with the ability of activity classification. The experimental results demonstrate that our approach can help IoT applications become smart: it achieved 92% accuracy on the activity classification .

As the Neural Knowledge based Smart IoT is at its early research stage, there are further research and refinement remaining to be done, some of them are:

- Further design and development of the framework.
- Further design and development of the knowledge representation model.
- Refinement and further development of the learning algorithms.

ACKNOWLEDGEMENT

The authors would like to thank the editors and anonymous reviewers for their valuable comments and suggestions on this paper. This work was supported by the Sichuan Science and Technology Program under Grant 2019YFH0185.

REFERENCES

Al-Ali, A. R. , Zualkernan, I. A. , Rashid, M. , Gupta, R. , & Alikarar, M. . (2018). A smart home energy management system using iot and big data analytics approach. IEEE Transactions on Consumer Electronics, 63(4), 426-434.

Burton, L., Dave, N., Fernandez, R. E., Jayachandran, K., & Bhansali, S. (2018). Smart gardening iot soil sheets for real-time nutrient analysis. Journal of The Electrochemical Society, 165(8), B3157-B3162.

Gubbi, J. , Buyya, R. , Marusic, S. , & Palaniswami, M. . (2013). Internet of things (iot): a vision, architectural elements, and future directions. Future Generation Computer Systems, 29(7), 1645-1660.

Lecun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. Nature, 521(7553), 436.

Lin, J., Yu, W., Zhang, N., Yang, X., Zhang, H., & Zhao, W. (2017). A survey on internet of things: architecture, enabling technologies, security and privacy, and applications. IEEE Internet of Things Journal, 4(5), 1125-1142.

Lokshina, I. , & Lanting, C. . (2019). A Qualitative Evaluation of IoT-Driven eHealth: Knowledge Management, Business Models and Opportunities, Deployment and Evolution. Hicss.

Mohammadi, M. , & Al-Fuqaha, A. . (2018). Enabling cognitive smart cities using big data and machine learning: approaches and challenges. IEEE Communications Magazine, 56(2), 94-101.

Sanin, C. , Haoxi, Z. , Shafiq, I. , Waris, M. M. , Caterine, S. D. O. , & Szczerbicki, E. . (2018). Experience based knowledge representation for internet of things and cyber physical systems with case studies. Future Generation Computer Systems, S0167739X17316965.

Sharma, N. , Singh, K. , & Goyal, D. P. . (2012). Is technology universal panacea for knowledge and experience management? answers from indian it sector. Communications in Computer & Information Science, 285, 187-198.

Siddiqui, I. F. , Qureshi, N. M. F. , Shaikh, M. A. , Chowdhry, B. S. , Abbas, A. , & Bashir, A. K. , et al. (2018). Stuck-at fault analytics of iot devices using knowledge-based data processing strategy in smart grid. Wireless Personal Communications.

Siow, E. , Tiropanis, T. , & Hall, W. . (2018). Analytics for the internet of things: a survey. Acm Computing Surveys, 51(4).

Siryani, J., Tanju, B., & Eveleigh, T. J. (2017). A machine learning decision-support system improves the internet of things' smart meter operations. IEEE Internet of Things Journal, 4(4), 1056-1066.

Tsai, C. W., Lai, C. F., Chiang, M. C., & Yang, L. T. (2014). Data mining for internet of things: a survey. IEEE Communications Surveys & Tutorials, 16(1), 77-97.

Wu, S. , Rendall, J. B. , Smith, M. J. , Zhu, S. , Xu, J. , & Wang, H. , et al. (2017). Survey on prediction algorithms in smart homes. IEEE Internet of Things Journal, 4(3), 636-644.

Zhang, H., Sanin, C., & Szczerbicki, E. (2016). Towards neural knowledge dna. Journal of Intelligent & Fuzzy Systems, 32(2), 1575-1584.