Detection of children's activities in smart home based on deep learning approach

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ABSTRACT
Monitoring behavior of children in the home is the extremely important to avoid the possible injuries. Therefore, an automated monitoring system for monitoring behavior of children by researchers has been considered. The first stepfor designing and executing an automated monitoring system on children's behavior in closed spaces is possible with recognize their activity by the sensors in the environment, collect data, and then use learning algorithms. In this paper, a deep learning algorithm to recognize and classify children activity in smart home is proposed which data collected from sensors in a smart environment. Experimental result on ARAS dataset indicates that this type of reorganization is highly effective and practical.

Keywords
deep learning, children activities, smart home ARAS.

1. INTRODUCTION
Children usually began walking between 9 and 16 months old and faced withthe risk of falling from furniture and stairs. Falling out of the window and the bed is one of the most important factors in child injuries. Therefore, a secure management to prevent injury is essential for children. One of the most challenging issues Categories daily activities is activities safe and dangerous activities [1,2,3]. Although many methods have been proposed for the detection of human activities, Human activity recognition is an important task and challenge in terms of detection accuracy. The combination of data from multiple sensors used to monitor the children's daily activities [4]. In [5], the two sensors mounted on the leg and wrist, in [6] a tri-axial accelerometer is mounted on the child's wrist and in another study multiple sensors and spectral analysis techniques were used to identify human activity [7]. By developing smart technologies in the field of network and sensors, the smart environments were designed. Through smart environment, the smart homes in the area of human activity recognition have attracted great attention. Two important technologies to identify human activities in the smart environments are used: machine vision and the use of the sensor. Sensors for gathering the raw data about the physiology body, physical activity and environment are used. Automatic detection of child activities using data from several sensors have benefits such as monitoring the child's growth, estimating energy expenditure, prevent childhood obesity, child safety at home and outside the home.

Activity detection is classifying problem based on sensors was considered on human body or environment. In many developed countries, supervision and simulation of physical activity is used to prevent obesity in children and adults. In [8], the methods of spectral analysis data sensors used to detect activities. Then quadratic separable analytics classifier trained using data and is used to detect Children's activities [9]. In [10] tri-axial accelerometer sensors and pressure sensor is used to detect Children's activities. Data tagged from the sensors connected to the leg and wrists of children 16 to 29 months old have been collected. Characteristics such as mean, standard deviation and the slope of the time-range sliding windows have been calculated for category and detection of child's daily activities. In [11] a tri-axial accelerometer and temperature sensor is used to detect activity in children. In this paper several sensors and GSM modem connection is used to oversee children's activity. The wireless receiver is used to receiving data collected by the sensors. In [12] a method to prevent drug allergy, drug interactions and children falling from height are provided. By using accelerometer sensor and shown on a LCD, Children's activity has been detected. Anything was displayed on the LCD with an alert is sent to the mobile Android. In this paper, a deep learning algorithm for automatic detection Children's activities in the smart home environment is offered. Next section describes the proposed system architecture.

2. RELATED WORK

Activity detection techniques have been widely researched and some of the findings focusing on smart home domain will be presented in this section. Before finding algorithms that could recognize activities in real time, research activities were focused on offline mechanisms which use static data sets, in which all the data is firstly stored and then analyzed. Hong and Nugent focus on segmenting sensor data to extract each segment of consecutive sensor events associated with a complete activity[12]. They detect using the toilet, taking a shower, leaving the house, going to bed and preparing meals. By taking into account correlations of locations, objects and sensors with activities being monitored, they propose three approaches to sensor stream segmentation: location-based approach, model-based approach and dominant centered model-based approach. All three algorithms showed similarly good performances for segmentation and activity classification. However, they point out that the increased prevalence of pervasive technologies such as mobile phones, tablet computers and wireless sensor networks could have an impact on these algorithms since they are all based on mappings between objects and activities, and between locations and activities[13].

Tao Gu et al. present a way to avoid usual supervised learning phase in the machine learning process for activity recognition. They base their algorithm on object-use fingerprints and test it on various everyday activities such as: making coffee, making phone calls, washing clothes, taking pills, reading books, just to mention a few. The main idea is to retrieve objects used in a specified activity from the Web and identify the relevance weight for each retrieved object. Since activities may share common objects, it is also necessary to mine a set of contrast patterns from object

terms and their relevance weights for each activity class. Segmenting data is done using the sliding window combined with ”MaxGap” and ”MaxGain” segmentation heuristic algorithms to determine the beginning and ending of activity.

The result shows that this recognition algorithm achieves precision of 91.4%, which is almost as good as hidden Markov model algorithm which includes a learning phase (93.5%)[14].

JieWan et al. implement a way to process sensor data and recognize activities in real-time. Most of the algorithms perform analysis offline, by using stored datasets which are good for researches, but in real-world environment data should be instantly processed so that the proper actions can be taken if needed. The authors concentrate on data segmentation in real time by using sensor and time correlation. Observed activities in this work were also usual daily activities in a smart home environment as listed earlier in this section. Different algorithms were tested for activity recognition, such as Bayesian network, decision trees, and Hidden Markov Models (HMM)[15]. It was proved that selection of the algorithm had a great influence on final results. Additionally, it was proved that segmentation has great impact on the capabilities of activity recognition algorithms. Reducing energy consumption on M2M devices (sensor nodes) is a very important aspect that needs to be considered especially when the devices are battery powered. Special attention towards energy consumption should be paid when deploying software on the devices. Wang et al present a distributed event detection approach using self-learning threshold. Along with reliable detection, the authors state that energy saving is another major challenge on Resource-constraint sensor nodes when designing such system. To tackle the issue with energy consumption, within their work they propose a timer-based node sleep scheduling to prolong network lifetime during the detection process. In most cases when solutions for activity detection in smart home environment were presented, two level event detection approaches was proposed. First level refers to activity detection on a sensor node, and the second level refers to gateway reaching a consensus among individual sensor node decisions about the activity. Also, activity detection made great improvements in the area of elderly people assisted living[16,17].

3. PRERPOCESS

The raw data obtained from the sensors must be processed before they can be used in the next step. Must of preprocessing methods contain segmentation and reduced in size. The data collected from the sensors are often dirty. Data preprocessing mainly including data cleaning to remove unwanted samples, interpolation of missing data and to deal with data conversion is to put data in the correct format. The raw data collected from sensors containing errors, noise and duplicate information. To reduce the effect of these problems, the data must be checked.

4. DIMENSION REDUCTTION

The dimension reduction is similar to extracting features that show important data characteristics. Dimension reduction feature vectors are done in such a way that relevant information is preserved. The aim of Reduction large volume of raw data is due to heterogeneous sensors and different type of sensor. A key factor for the performance of smart homes is ability to extract useful information and summaries of raw data sensors.

5. FEATURE EXTRACTION

Features are key properties of amounts the data quantity. A few of the features extracted from the data obtained from sensors is useful to improve the accuracy of the algorithm because in times and computational cost effected and reduce them. Features extracted from the raw data have unrelated information that can affect to system performance. Many methods to reduce the adverse effects such as dependency-based feature selection, support vector machine feature selection and Forward-Backward Sequential Search is proposed.

6. DEEP LEARNING ALGORITHM

A supervised learning algorithm was introduced in 2006 by Hinton for a class of deep generative models that they called deep belief networks (DBNs). In this paper, DBNs are used for our researches which have four hidden layers. The number of the units in each layer is 10,100,300 and 300 that shown clearly in figure1.

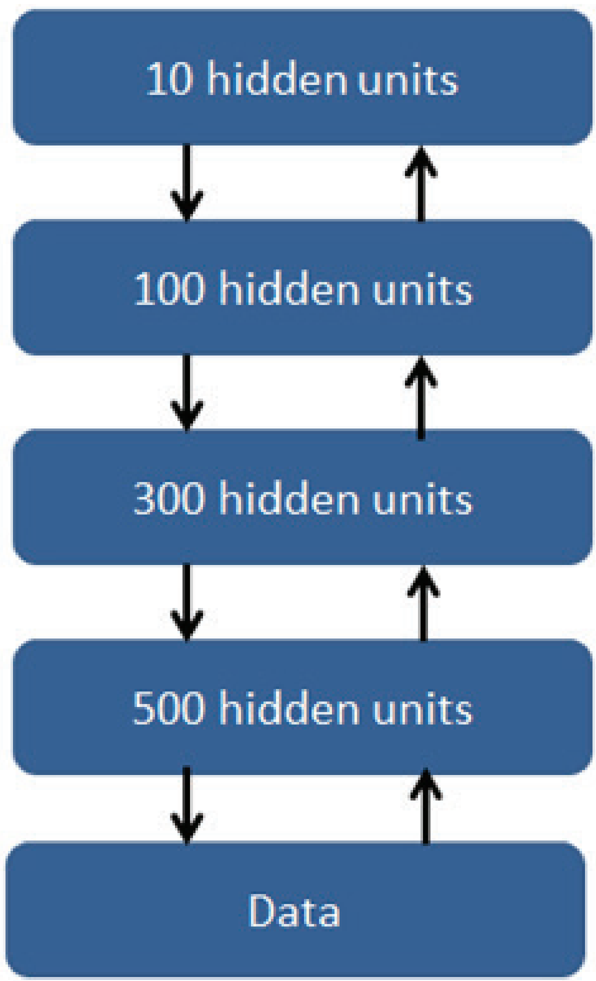

Figure1. Deep Network

Every deep belief networks has a lot of layers that are built using RBMs. Each RBM contains one stochastic hidden layer and a stochastic visible layer [13], [14]. As shown in Fig2 and Fig3. Each unit in RBM has an energy function and the nodes in one layer only connect with the nodes between the layers and have no connection and conditionally independent in the same layer [9], [11].

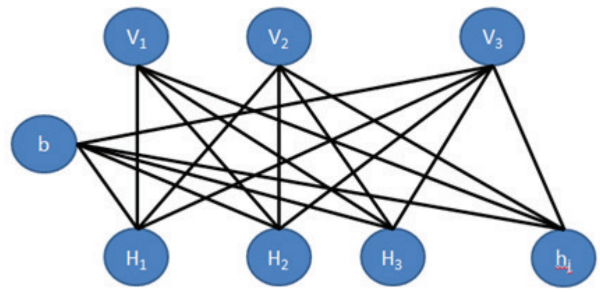

Figure2. Restricted Boltzmann machine

To generate data from a RBM, we can start with a random state in one of the layer and then perform other sampling. In this algorithm, all the units' value should be updated independently and the sampling can repeat for many times until we get our ideal final result. In a RBM, the concept that each unit has different activation energy is used. The proposed network is divided into several RBM. The training data entered to the first RBM and RBM is trained. Then RBM hidden layer converted to the second layer becomes visible. Features learned in the first RMB are considered as second RBM input. These Training steps until the probability of top layer obtained are repeated. After calculating possibilities and weights for each layer, the next step begins. In this step, the actual data entrance to network and data products from top to bottom process. The aim of paper is to find the weights which can minimize error rate. As shown in Figure 3, learning process method is proposed, where the network is divided into several RBM. Each layer of upper layer is independent and is connected to the bottom layer to make a RBM. The training data are placed in RAM to be trained RBM. Then, the first hidden layer RBM becomes second layer can be visible. As you can see training process is top to down.

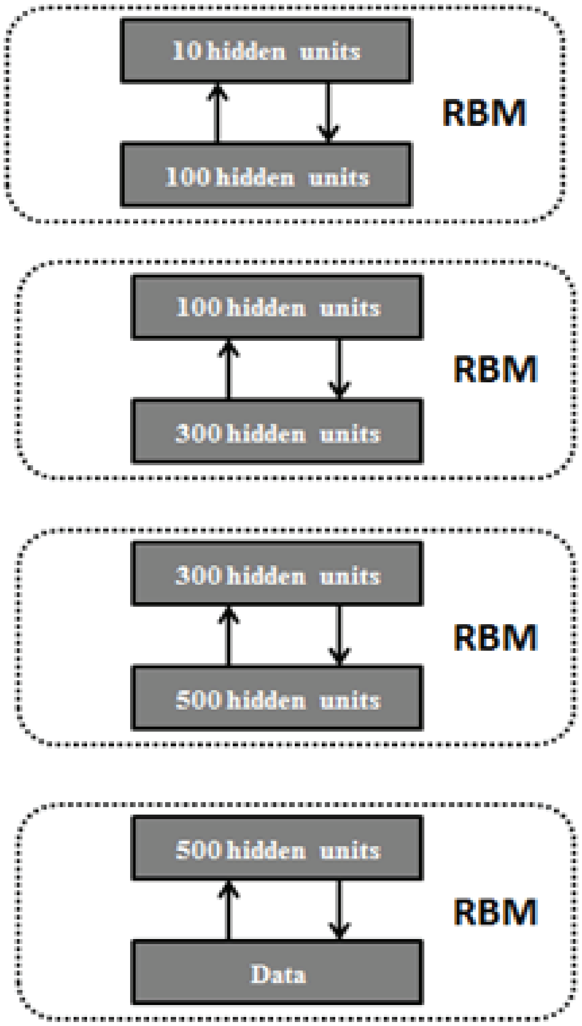

Figure3. Fine Training

According to compare, the back propagation network algorithm is a valid algorithm to train our deep learning network. In back propagation network, we put the training data into the network, generate the inferred data. Then the difference between these two sets of data is fed back, go through all the layers in the network.

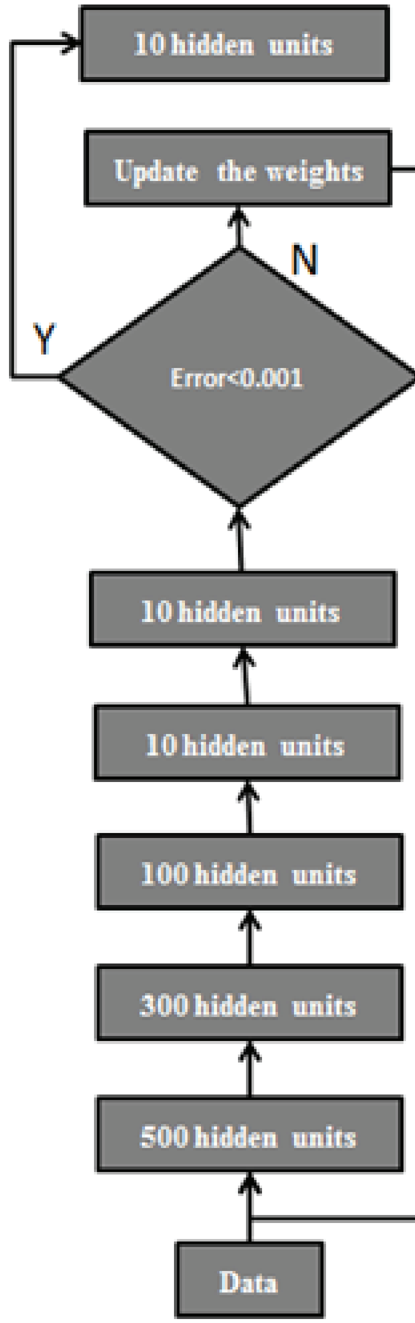

Figure4. Pre Training

Then we can update the weights in every layer by calculating the differences that generated from the step we discussed above. In our algorithm, we use back propagation algorithm to fine turning our network after pre-training it by RBMs. After pre-training process, the weights are initialed for the next phase, the fine turning. At last, we get the final weights and bias of our model.

7. DEEP LEARNING ALGORITHM

In this paper, ARAS dataset [13] for the implementation of deep learning networks have been used. This dataset offers set of signals that are used to diagnose human activities. These signals by sensors that are embedded in the home environment have been achieved. These dataset 3000 different activities within a month for two smart homes and several volunteers provide. Due to limitations dataset related to activities of children in smart home, activities similar to the activities of children in this dataset includes eating, sleeping, eating, sitting, standing, falling, etc. are used. Activities are divided into four categories and accuracy categories of our method for these four categories are shown in the table1.

Table1. Activity recognition rate

activity	1	2	3	4
accuracy	0.54	0.68	0.65	0.67

8. CONCLUSION

Therefore, the data collected from the sensors and then pre-processed. Then for categorize activities, Dimension reduction and feature extraction method based on deep belief networks is used.Experimental results in ARAS Dataset showed the accuracy of the proposed method is acceptable.

REFERENCES

1) A. M. Khan, Y.-K. Lee, S. Y. Lee, and T.-S. Kim. (2010, Sep.). A triaxial accelerometer-based physical-activity recognition via augmentedsignal features and a hierarchical recognizer.Trans. Info. Tech. Biomed.,[Online]. 14(5), pp. 1166–1172, Available: http://dx.doi.org/10.1109/TITB.2010.2051955

2) N. Li, Y. Hou, and Z. Huang. (2011). A real-time algorithm based on triaxial accelerometer for the detection of human activity state. in Proc. 6th Int. Conf. Body Area Netw., ser. BodyNets '11. ICST,Brussels, Belgium, Belgium: ICST (Institute for Computer Sciences,Social-Informatics and Telecommunications Engineering), [Online]. pp.103–106, Available: http://dl.acm.org/citation.cfm?id=2318776.2318801

3) A. G. Bonomi. (2011). Physical activity recognition using a wearable accelerometer. inProc. Sens. Emot., ser. Philips Research Book Series,J. Westerink, M. Krans, and M. Ouwerkerk, Eds., Springer Netherlands,[Online]. vol. 12, pp. 41–51. Available: http://dx.doi.org/10.1007/978-90-481-3258-4_3

4) A. Fleury, M. Vacher, and N. Noury, "Svm-based multimodal classification of activities of daily living in health smart homes: Sensors, algorithms,and first experimental results,"IEEE Trans. Inf. Technol. Biomed., vol. 14,no. 2, pp. 274–283, Mar. 2010.

5) C. Zhu and W. Sheng. (2009). Multi-sensor fusion for human daily activity recognition in robot-assisted living. in Proc. 4th ACM/IEEE Int. Conf. Human Robot Int., ser. HRI '09. New York, NY, USA: ACM, [Online].pp. 303–304, Available: http://doi.acm.org/10.1145/1514095.1514187

6) Nam, Yunyoung, and Jung Wook Park. "Child activity recognition based on cooperative fusion model of a triaxial accelerometer and a barometric pressure sensor." IEEE journal of biomedical and health informatics 17.2 (2013): 420-426.

7) Boughorbel, Sabri, et al. "Child-activity recognition from multi-sensor data."Proceedings of the 7th International Conference on Methods and Techniques in Behavioral Research. ACM, 2010.

8) Livingstone, M. B. E., Childhood obesity in Europe: a growing concern. Publich health nutrition 4(1a), (2001), 109-116.

9) Boughorbel, Sabri, et al. "Child-activity recognition from multi-sensor data."Proceedings of the 7th International Conference on Methods and Techniques in Behavioral Research. ACM, 2010.

10) Nam, Yunyoung, and Jung Wook Park. "Child activity recognition based on cooperative fusion model of a triaxial accelerometer and a barometric pressure sensor." IEEE journal of biomedical and health informatics 17.2 (2013): 420-426.

11) Nehete, JayashreeOnkar, and D. G. Agrawal. "Real time Recognition and monitoring a Child Activity based on smart embedded sensor fusion and GSM technology."

12) Kushbu, Design and Implementation of Child Activity Recognition, Drug Interaction Detection and Update of Drug Allergies, International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering,2014.

13) http://www.cmpe.boun.edu.tr/aras/

14) Hong, X., Nugent, C.D.. Segmenting sensor data for activity monitoring in smart environments. Personal Ubiquitous Comput2013; 17(3):545–559. doi:10.1007/

s00779-012-0507-4.

15) Gu, T., Chen, S., Tao, X., Lu, J.. An unsupervised approach to activity recognition and segmentation based on object-use fingerprints. Data KnowlEng2010;69(6):533–544. doi:10.1016/j.datak.2010.01.004.

16) Wan, J., O'Grady, M.J., O'Hare, G.M.P.. Dynamic sensor event segmentation for real-time activity recognition in a smart home context.Personal and Ubiquitous Computing 2014;19(2):287–301. doi:10.1007/s00779-014-0824-x.

17) Wang, Y., Wang, D., Chen, F., Fang, W.. Efficient event detection using self-learning threshold for wireless sensor networks. WirelNetw2015;21(6):1783–1799. doi:10.1007/s11276-014-0885-9.

18) Mekikis, P.V., Athanasiou, G., Fischione, C.. A wireless sensor network testbed for event detection in smart homes. In: 2013 IEEE

19) International Conference on Distributed Computing in Sensor Systems. 2013, p. 321–322. doi:10.1109/DCOSS.2013.36.

20) Benmansour, A., Bouchachia, A., Feham, M.. Human activity recognition in pervasive single resident smart homes: State of art. In:

21) Programming and Systems (ISPS), 2015 12th International Symposium on. 2015, p. 1–9. doi:10.1109/ISPS.2015.7244997.