Horizontal Slicing Clustering Based Movement Detection Method for IoTs

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Abstract. Movement detection in Internet of Things (IoTs) has been widely used in many fields, such as valuables monitoring, safety protection and empty-nesters care. Monitoring by videos, GPS and ultrasonic is the most common method to address the movement detection in IoTs. However, these efforts are circumscribed because they need the support of the special equipment, such as cameras, infrared equipment and ultrasonic facilities. It is significant to detect the movement in IoTs systems without additional equipment and ensure its high detection precision. Therefore, in this paper we derive an innovative method called Horizontal Slicing Clustering (HSC) to detect the movement in the IoTs. Received Signal Strength Indicator (RSSI) data are the network parameters which are utilized in this method. The simulation results show their effectiveness in movement detection.

Keywords: Internet of things (IoTs) · Movement detection
Horizontal slicing clustering (HSC)
Received signal strength indicator (RSSI)

1 Introduction

IoTs is the network of physical objects, vehicles, buildings and other items embedded with electronics, software, sensors, and network connectivity that enables these objects to collect and exchange data [1]. The main supports of IoTs are telecommunication technology, internet technology, electronic technology and information processing technology. IoTs have been applied in various social core departments with the rapid development. In these departments, movement detection is a very valuable topic. In factories, movement detection can achieve the monitoring of valuable instruments and equipment; in hospitals, medical workers can employ movement detection technology to care patients. At present, the movement detection technology has a wide range of research. Many researchers have accomplished movement detection through the Video [2], GPS [3], red line [4], ultra sound wave [5], RF [6] and so on. Although many

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movement detection systems have been proposed, few of them can be used in daily living setting because of the limitation of relevant equipment. The expected result is to achieve movement detection without additional equipment. So devices-free methods for movement detection have attracted a lot of attention. The projects about passive means for movement detection have been given [7, 8]. In current devices-free efforts, CSI data are chosen as a better choice compared with RSSI data because the former are more stable than the latter. Current studies about RSSI data based methods are unable to obtain good efforts because of their fluctuation. However, CSI can only be collected from few wireless devices, so its application is very circumscribed. Thus, a high-precision and widely applicable movement detection method for IoTs system is needed. In this paper, Horizontal Slicing Clustering (HSC) method is proposed to determine whether movement exists in the working environment of IoTs. We apply this method to analyze the RSSI data which can be collected from any wireless devices of IoTs. Analyzing the feature of the RSSI data through HSC method when the IoTs system is working, then we can judge the actual status of the working environment.

2 Related Work

2.1 RSSI

RSSI data are used as major metrics in this paper. RSSI data are frequently used in IoTs to indicate the strength of communication signals between wireless devices. The distance between antennas will influence the RSSI value directly [9]. In [9], RSSI is defined as follows:

$$RSSI = 10 \cdot \log \frac{P_{RX}}{P_{\mathrm{Ref}}} \tag{1}$$

where PRef is typically taken as 1 mW and PRx is the remaining power of the wave at the receiver. RSSI is relatively stable if there are no movement or other changes in the environment. RSSI data can get influences from a number of factors such as reflection from objects, electromagnetic fields, diffraction, and other multipath effects [10]. Because of these effects, the movement in the environment is an important factor which can influence the RSSI data. It has been proved that the movement of human will affect the propagation of wireless signals [11, 12]. When someone moves around the communicating environment, the reflection, diffraction and other factors will be changed, so the feature of RSSI data will be different. Thus, we can determine the movement by the respective feature of different RSSI data. One of the desirable reasons that we select RSSI data in this paper is that the indicators can be collected easily from any wireless devices in IoTs when they communicating with others.

Obviously, it is very difficult to determine the movement only by the original RSSI data because they might overlap each other. In this paper, we use HSC method to deal with the indistinguishable RSSI data and get the differentiable HSC curves. Hence, detecting the movement in the environment where the IoTs system is deployed. Moreover, using only RSSI data to realize movement detection is challengeable because RSSI data can be affected by other factors such as the interferences from the noise. In order to improve the effectiveness of the analysis, adaptability and robustness of algorithm are needed.

2.2 Mathematical Morphology

In this paper, an innovative method called Horizontal Slicing Clustering (HSC) is presented to detect the movement in the communicating environment. In order to establish the detection method, we use tools taken from Mathematical Morphology (MM). MM is based on set theory, lattice theory, topology, and random functions [13] and it is most commonly used for digital image processing. Meanwhile, it can be employed as well on graphs, surface meshes, solids, and many other spatial structures [14]. [15, 16] introduced the application of MM to deal with the clustering of functional data. MM operators extract the relevant structures of the set under study by probing it with another set of a known shape called structuring element (SE) [17]. The SE can be any kind of shape that researchers are interested in. Erosion, dilation, opening and closing are four basic operations in MM. The erosion of the binary image A by the structuring element B is defined by:

$$A \Theta B = \left\{ x \mid (B)_{\mathrm{x}} \subseteq A \right\} \tag{2}$$

Where x is a vector and (B)x is defined as:

$$(B)_{\mathrm{x}} = \{ \mathrm{b} + \mathrm{x} \mid b \in B \} \tag{3}$$

The dilation of A by B is given by the expression:

$$A \oplus B = \left\{ x \mid \left[(B)_{\mathrm{x}} \cap A \right] \neq \phi \right\} \tag{4}$$

The opening of A by B is obtained by the erosion of A by B, followed by dilation of the resulting image by B:

$$A \circ B = (A \Theta B) \oplus B \tag{5}$$

The closing of A by B is obtained by the dilation of A by B, followed by erosion of the resulting structure by B:

$$A \bullet B = (A \oplus B) \Theta B \tag{6}$$

3 Horizontal Slicing Clustering

In this section, detailed explanation of Horizontal Slicing Clustering (HSC) method is presented. The inspiration of HSC algorithm is from mathematical morphology. An HSC function is a process of slicing. Slicing is a Mathematical Morphology

(MM) based operation. The key point of HSC method is slicing the original signals with different size of the Structuring Elements (SE) and clustering the sliced results. Sliced results are generated by successively dilating or eroding the target image by increasing the size of SE. In this paper, we take the unit square as the original SE because RSSI data are integers. The increasing speed of the SE is 1 at each time. In order to analyze the RSSI data through HSC method, the RSSI data collected by receivers will be transformed to step function. So we can get the RSSI data based step curve in two-dimension. The horizontal axis shows the simulation time and the vertical axis represents the signal strength. We call the step curve as RSSI curve. By using incremental SE to slice the RSSI curve horizontally, the different structures of RSSI curve can be separated. By clustering the sliced results, we can get the proportional distribution of the different structures from the RSSI curve. Main steps of HSC function are as follows:

- Step(a): Calculating the total areas of the original RSSI curve S0.
- Step(b): Setting the unit square as basic SE.
- Step(c): Using current SE to slice the RSSI curve. If there are peaks match the size of current SE, counting the total sliced areas Y(n) and removing these sliced area from RSSI curve. If no peak matches the current SE, regarding the Y(n) as 0.
- Step(d): Calculating the ratio between the summation of all sliced areas so far and the S0 and we can get HSC(i). We call the summation of all the sliced areas so far as Section Score (SS).
- Step(e): Adding one unit of the SE horizontally to enlarge it and repeat steps (c) and (d) until all the areas of the RSSI curve are sliced.

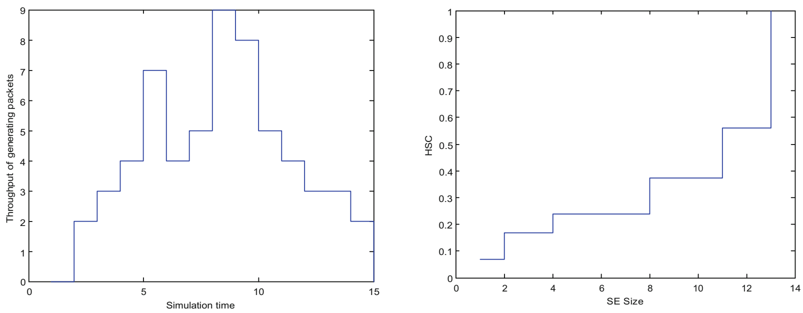
The HSC(i) is defined as:

$$HSC(\mathrm{i}) = \frac{SS(\mathrm{i})}{S_0} \tag{7}$$

Where SS(i) is defined as:

$$SS(\mathrm{i}) = \sum_{n=1}^{i} Y(n) \tag{8}$$

In Fig. 1, an example of HSC function is illustrated. A random signal was generated by Matlab, where S(x) = [0, 0, 2, 3, 4, 7, 4, 5, 9, 8, 5, 4, 3, 3, 2, 0]. Figure 1(a) is the step function of the random signal. Applying HSC algorithm and we can get the HSC curve, as shown in Fig. 1(b). In this paper, we employ HSC algorithm to extract the structural feature of RSSI data to determine whether there is movement in the environment. For more detail of HSC method, we generate Table 1. Sliced areas Y(n) are generated by Mathematical Morphology (MM) based slicing. After all the areas have been sliced by incremental SE, we gather the information together and calculate their Section Score(SS). Then we can get HSC by dividing SS(i) to the total area. In our experiment, we use this HSC method to process the RSSI data of wireless nodes when they communicating in different situations.



(a) Stepwise function of the random signal (b) HSC function of the random signal

Fig. 1. Illustrative example of HSC function

Table 1. Illustrative example of HSC.

SE size	Matched numbers	Sliced areas	Section score	HSC
1	4	4	4	4/59
2	3	6	10	10/59
3	0	0	10	10/59
4	1	4	14	14/59
5	0	0	14	14/59
6	0	0	14	14/59
7	0	0	14	14/59
8	1	8	22	22/59
9	0	0	22	22/59
10	0	0	22	22/59
11	1	11	33	33/59
12	0	0	33	33/59
13	2	26	59	59/59

4 Experimental Details

In IoTs system, transmitters broadcast wireless signals, meanwhile, receivers in the similar system collect the data. We name the transmitters as Access Points (APs) and receivers as Monitoring Points (MPs) hereafter. The APs can be typically access points, such as routers which can transmit wireless signals. And the MPs could be any existing wireless devices in living setting, such as smartphones and smartbands. In our experiment, we used a router and three smartphones which were the most universal devices in daily living setting as the experimental equipment. The router was employed as AP and the smartphones were used as MP and named MP (1), MP (2), MP (3) respectively. The operating system of the smartphones was Android. Android system is a kind of open source operating system based on Linux. The system was running in 2.4 GHz. We opened the wireless hotspot function of the router so it could build a small communicating system as a kernel. Many interested activities often happened in several seconds, so we increased the sample rate to 10 packets per second in order to capture the changes of the signals by the short time activities. There were two scenarios in dormitory and students' park respectively in our experiment. Through the results generated from different environments, we could verify the environmental adaptability of our algorithm.

The topologies of the nodes in the experiments can be seen in Fig. 2. In the first scenario, we collected RSSI data from two cases separately. In case one there was no movement in the dormitory and in case two an experimenter opened the door and moved around the dormitory. The AP was deployed in the center of the dormitory and the MPs was deployed around the AP. In the second scenario, we deployed a small IoTs system in the students' park and the RSSI data were collected by the MPs again. There were also two situations in the second scenario in which the first was that the system was deployed at night when the environment was quiet and there was no movement there, and the second was collecting RSSI data at twelve o'clock when students came home from school and the students' park was busy. The AP was deployed in the center of students' park and the MPs was also around the AP. Each MP recorded 2000 successive data points in each scenario, half of which were collected from the dynamic environment and the other half were from the static situation.

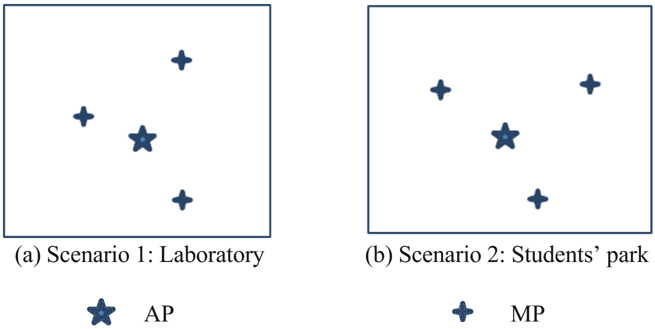
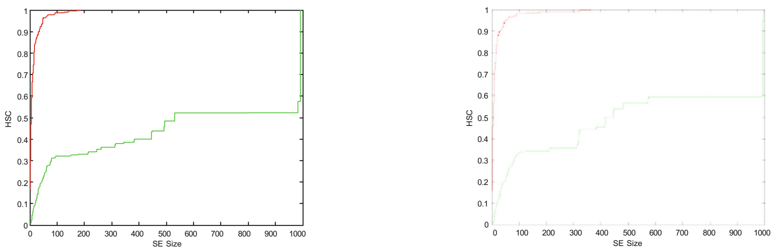


Fig. 2. Topologies of IoTs

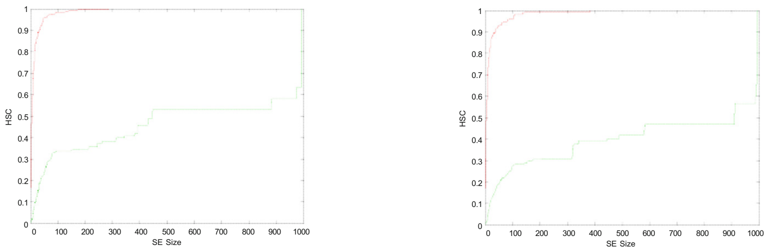
5 Result Analysis

The primary motivation is detecting movement in the communicating environment without additional equipment. In our experiment, by comparing the HSC curves of RSSI data collected by the smartphones in different situations, we can successfully and clearly differentiate their feature through HSC curves, which makes it possible to determine whether there is movement in the environment. Figure 3 shows HSC curves in different situations. We gathered the HSC function of RSSI data received by MP (1), MP (2) and MP (3) when the status of environment is different. The green curves show the static situation and the reds represent the dynamic status. It is very clear to observe that the HSC curves have been successfully differentiated into two different clusters in



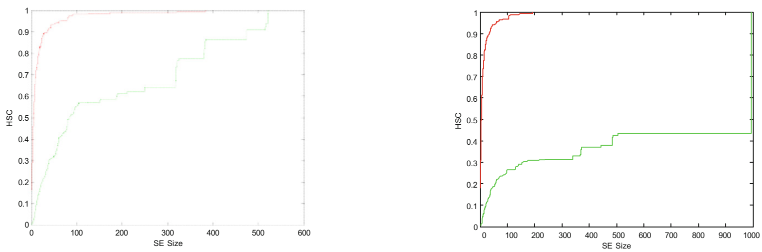
Scenario 1: Dormitory
Scenario 2: Student' park

(a) HSC Function of Received RSSI of MP (1)



Scenario 1: Dormitory
Scenario 2: Student' park

(b) HSC Function of Received RSSI of MP (2)



Scenario 1: Dormitory
Scenario 2: Student' park

(c) HSC Function of Received RSSI of MP (3)

Fig. 3. HSC results of RSSI

each scenario. The shapes of HSC curves are dissimilar when the IoTs system communicates in different situations, which makes it possible to determine whether there is movement by briefly observing and analyzing the shapes of HSC curves.

Assume an IoTs system which works in a static condition. At a certain moment, the movement suddenly appears in the environment. Then the HSC curves of RSSI data will change and be different. By differentiable HSC curves, the communication condition can be determined. From the results of two different scenarios, the environmental adaptability of HSC method can be shown.

6 Conclusion

In this paper, a practical problem in IoTs is presented, which is how to determine the movement in the environment of IoTs without additional equipment. HSC method is presented to solve this problem. The detailed explanation of HSC method is presented in this paper. Finally, our experiment results indicate that the HSC method can translate the indistinguishable RSSI data into the differentiable HSC curves and have some ability of environmental adaptability. Hence, movement in the communicating environment can be effectively determined.

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References

1. Matern, D., Condurache, A., Mertins, A.: Automated intrusion detection for video surveillance using conditional random fields. In: International Conference on Machine Vision Application, pp. 298–301 (2013)
2. Kichun, J.: Interacting multiple model filter-based sensor fusion of GPS with in-vehicle sensors for real-time vehicle positioning. IEEE Trans. Intell. Transp. Syst. **13**(1), 329–343 (2012)
3. Want, R., Hopper, A., Falcao, V., et al.: The active badge location system. ACM Trans. Inf. Syst. **10**(1), 91–102 (1992)
4. Priyantha, N.B., Chakraborty, A., Balakrishnan, H.: The cricket location-support system. In: Proceedings of the 6th Annual International Conference on Mobile Computing and Networking, pp. 32–43 (2000)
5. Ye, H., Ektesabi, M.: RF indoor intrusion detection system. Lecture Notes in Engineering and Computer Science. DOAJ (2008)
6. Selvabala, V., Ganesh, A.B.: Implementation of wireless sensor network based human fall detection system. Procedia Eng. **30**, 767–773 (2012)
7. Xiao, J., Wu, K., Yi, Y., Wang, L., Ni, L.M.: FIMD: Fine-grained device-free motion detection. In: IEEE 18th International Conference on Parallel and Distributed Systems (ICPADS), pp. 229–235 (2012)
8. Zhang, Z., Lu, Z., Saakian, V., Qin, X., Chen, Q., Zheng, L.-R.: Item-level indoor localization with passive UHF RFID based on tag interaction analysis. IEEE Trans. Ind. Electron. **61**(4), 2122–2135 (2014)
9. Grossmann, R., Blumenthal, J., Golatowski, F., Timmermann, D.: Localization in zigbee-based sensor networks. In: Proceedings of the 1st European ZigBee Developers Conference, Munchen, Germany (2007)
10. Zhang, D., Ma, J., Chen, Q., Ni, L.M.: An RF-based system for tracking transceiver-free objects. In: 2007 Fifth Annual IEEE International Conference on Pervasive Computing and Communications, PerCom 2007, pp. 135–144. IEEE (2007)

11. Youssef, M., Mah, M., Agrawala, A.: Challenges: device-free passive localization for wireless environments. In: Proceedings of the 13th Annual ACM International Conference on Mobile Computing and Networking, pp. 222–229 (2007)
12. Serra, J.: Image Analysis and Mathematical Morphology. Academic Press, London (1982)
13. Soille, P.: Morphological Image Analysis: Principles and Applications. Springer, Berlin (2003)
14. Ayala, G., Gaston, M., Leon, T., Mallor, F.: Measuring dissimilarity between curves by means of their granulometric size distributions. In: Functional and Operatorial Statistics. Contributions to Statistics, pp. 35–41 (2008)
15. Leon, T., Ayala, G., Gaston, M., Mallor, F.: Using mathematical morphology for unsupervised classification of functional data. J. Statist. Comput. Simul. **81**(8), 1001–1016 (2011)
16. Gaston, M., Leon, T., Mallor, F., Ramirez, L.: A morphological clustering method for daily solar radiation curves. J. Solar Energy **85**, 1824–1836 (2011)