Exploring the role of sports APP in (campus fitness) intelligent solutions using data fusion algorithm and internet of things

Chao Zhu

Department of Physical Education,
Beijing Union University,
Beijing 100101, China
Email: zhuchao@buu.edu.cn

Abstract: The purposes are to study how the multi-sensor Internet of Things (IoT) data fusion algorithm calculates in data fusion systems and improves the systems' fusion efficiency. An improved Weighted Least-Squares (WLS) algorithm is proposed for IoT data fusion, and how it processes massive data in a multi-sensor system is studied. Accordingly, a multi-sensor system for sports fitness is designed based on a data fusion algorithm. First, the purposes and demand for sports Application (APP) are analysed, to understand the problems and necessary improvements of such APP. Then, the implementation of the IoT and the classification of the data fusion algorithm of the IoT are explored. The WLS method is selected through comparison, and its implementation process and the data processing process are analysed and explained. Finally, the sports fitness system based on the IoT data fusion algorithm is designed and analysed. The results show that the wireless communication of a multi-sensor data fusion system is feasible and reliable. The variances calculated through the WLS method and the Arithmetic Mean (AM) method in data fusion are compared. The former value is about one-thousandth of the latter value, indicating that the data fusion based on WLS is advantageous over the traditional data fusion.

Keywords: IoT; internet of things; multi-sensors; data fusion; weighted least-squares method; intelligent solutions.

Reference to this paper should be made as follows: Zhu, C. (2022) 'Exploring the role of sports APP in (campus fitness) intelligent solutions using data fusion algorithm and internet of things', *Int. J. Grid and Utility Computing*, Vol. 13, No. 1, pp.40–48.

Biographical notes: Chao Zhu graduated from Capital Institute of Physical Education in 2006, postgraduate, sports training, football teaching and training direction. He is a c-level coach of the Chinese Football Association, a junior coach of the Chinese Football Association futsal, and a first-level referee of the national football association. He is mainly responsible for the teaching of football, table tennis, health education for college students, Olympic education and other courses. He is good at teaching and training of football and table tennis. Now he is the head coach of Beijing Union University football Team (Group B).

1 Introduction

China's social industries are in the stage of rapid and in-depth development. Education, in particular, is an important joint of social progress and talent output. Concurrently, the pace of living, working, and learning has accelerated, the intensity has multiplied, and all kinds of pressures are squeezing in. In comparison, students' physical conditions are on a continuous decline due to a lack of systematic and effective physical training and an unreasonable curriculum in schools (Guo, 2020). Therefore, it is crucial to set up a systematic and effective physical fitness program to enhance students' physical quality. Students' self-consciousness and willingness to participate in sports are also the key to their physical fitness improvement. The economic and technological boom has brought an explosive development to the mobile internet and mobile Applications (APPs). Simultaneously, various sports fitness APPs have come into being, and their application scope is expanding continuously. Sports APPs are particularly loved and welcomed by many people, including students, for their novel fitness methods. By monitoring users' sports fitness and exercise data, formulating specific fitness plans, and providing timely guidance and a social platform, these sports APPs enable users to socialise during bodybuilding and exercising. Thus, the traditional fitness model is altered. With the in-depth development of IoT, the application of digital APPs in the traditional fitness and exercise model brings forth many favourable effects, which has an infinite development space (Liu, 2017).

Various cutting-edge technologies have been integrated into the Internet of Things (IoT), which can perceive position, collect features and analyse states of objects. The data fusion technology can analyse, identify, and process big data, and clean redundant, false, uncertain, or incomplete information in massive data. In sports data sensing and analysis, data fusion technology has a broad application prospect. IoT is often composed of many sensor networks, so the number of nodes and related information is also massive. Ding et al. (2019) studied the attributes of IoT data and proposed many requirements for IoT data fusion, including security and privacy. Qi et al. (2020) systematically studied the problem of physical activity identification and measurement from the perspective of physical activity data collection and model verification based on new 3D (three dimensional) dynamic IoT. Torres et al. (2020) proposed a multi-layer data fusion architecture Hydra to improve sensor accuracy, identify application target events, and make more accurate decisions. Thus, most research on data fusion of the IoT is aimed at the expansion of the data fusion algorithms, but there is no application in sports activity sensing data. Here, the sports APP is comprehensively analysed based on sensor data from the perspective of the campus fitness intelligent system.

Based on the current social development and research, to systematically and effectively apply sports APPs on the campus, the IoT data fusion technology is utilised and studied to provide students with campus fitness solutions and encourage them to participate more in sports. The results have practical significance for improving students' physical and comprehensive quality and provide a reference for the innovation and development of college sports in China.

2 Method

2.1 The purpose and demand analysis of sports APP on campus

People's behaviour is purpose-guided. Meanwhile, the purpose is orientational, which can determine how strongly people behave and how long they persist. Therefore, to study users' purpose in sports APPs can help understand their driving force to better implement sports APP for fitness exercise. The types of sports fitness are diverse, so are the purposes of users. These APPs are mainly used by college students, while other groups, such as office workers, only account for a few. College students have more free time than other groups of people, they have more extracurricular time, and they can use the APPs in their physical education classes, maximising the utilisation rate of sports APP.

Most college students use APPs for exercise and fitness, weight loss and beauty-shaping in terms of the purpose of use. This indicates that college students attach much importance to their health and physical fitness. It also reflects that the overall physical quality and health of college students in China are relatively low, and many people are overweighted. Besides, some students use the APPs to foster exercising habits, improve their sports skills, access fitness knowledge, and understand the development and changes in sports. A small group of users uses these APPs to meet new friends who are interested in sports and fitness, or for entertainment purposes. Although the purposes of men and women using sports APPs are different, there is little difference in the number of sports APP users between men and women on the whole.

From the perspective of function selection, users' selection diversifies according to the APP's functions and purposes. Most students choose the sports record function, indicating a higher demand for sports and sports ranking. Many users also choose the functions of weight loss and beauty-shaping, healthy diet plans, exercise and fitness plans and fitness skill teaching. Comparatively, marginal applications, such as social networking and entertainment, are chosen by a few users.

Unlike the single functioned APPs that are mature already, the demand for APP functions becomes personalised and diversified because of students' need for self-improvement. One of the most needed functions is the specific and feasible private fitness program, designed to help users achieve their set goals. Besides, functions, such as health monitoring, systematic knowledge supply and providing simple and effective skills are needed to help them train and shape themselves precisely and effectively. A small number demand sports peripheral product of users.

The existing problems and the orientation of sports APP development are explained, based on the above analysis on the purpose and demand of sports APP users on campus, which helps APPs provide high-quality intelligent solutions.

2.2 Data fusion algorithm for IoT

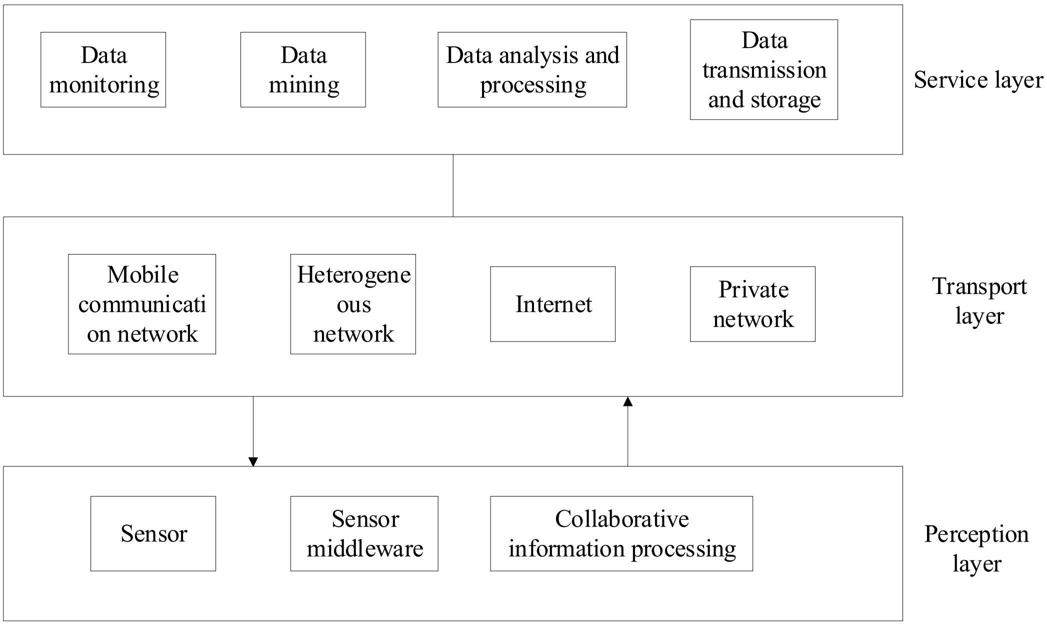
The IoT is established on network communication, and it is an important component of the new generation of information technology. It realises the interconnection between things, things and people and people and people, as shown in Figure 1.

The IoT is implemented through data collation and analysis, and the data are acquired through the sensor nodes set in the monitored area. There are intersections between sensors to ensure that the data in the monitoring area will not be missed, making more accurate and complete monitoring. Many problems await solution in this process: sensor nodes not only collect but also transmit data, two-way work shortens their service life; network resources are wasted by data aggregation and collection; moreover, the intersected data increases transmission repeatability and reduces the transmission efficiency (Nesa and Banerjee, 2017). Therefore, it is important and necessary to fuse the data in the implementation of the IoT.

Data fusion implementation is diverse, including digital and non-digital information, precise and fuzzy, synchronous and asynchronous (Chen, 2017), data fusion features and inherent attributes and data supplements. Data fusion deals with different dimensional information, and the fusion method varies accordingly, ensuring the fusion data quality.

The IoT is a network that connects things with things, things with people and people with people, and transmits the interoperability data information between them. Many aspects should be considered in data fusion: the selection of data fusion nodes, a well-chosen node reduces energy and time consumption; the time selection of data fusion, data fusion will be lost or delayed due to inappropriate timing (Saranya and Fatima, 2020); finally, data fusion method directly affects the fusion results. Besides, data fusion in IoT highlights its real-time characteristics. A high real-time response is required when collecting feature data to ensure sufficient transmission time and fusion analysis for the collected feature data (Dautov and Distefano, 2017).

Figure 1 Structure of the IoT



A specific data fusion algorithm fuses the data to obtain the final processing result, which is much more accurate and reliable than the single data result (Venkatesh et al., 2017). There are many data fusion algorithms, and the system can select them accordingly. (1) Weighted Least-Squares (WLS) method: different weights are assigned to the data, based on the least-squares method, reduce the effect of error data on the results. (2) The fuzzy theory algorithm, which unifies and processes all the data after data fuzzification, is suitable for multi-sensor data fusion. (3) Neural network algorithm processes data the same way as the human brain operates, with high fault tolerance and strong adaptability. The WLS method is selected through comparison, which can process the collected initially data and is suitable for dynamic data systems, meeting the system's real-time requirements (Esposito et al., 2018). The corresponding weights are assigned to the data according to the accuracy of measurement and monitoring of different sensors. Finally, the overall estimation is obtained by the mutual fusion of different regions. When the non-periodic environmental parameters, such as temperature and humidity, change little, this algorithm can prevent environmental fluctuations from affecting the data fusion results.

The sensor monitors the temperature, humidity, harmful gas concentration, and other variable data, which frequently change in the application. To transmit all these data waste resources (Li et al., 2018); hence, the improved WLS method is used to filter the data and reduce the redundant data and the cost. The WLS method fuses the data of similar sensors, then transmits the fused data, determines whether the time occurs through the preset threshold, and sends the report (He et al., 2019). The key of the algorithm is to assign the weight value. Per requirements of sensor monitoring accuracy, either the Arithmetic Mean (AM) or WLS method can be chosen. The AM method processes data directly, which has a few drawbacks, such as weak anti-interference ability and unable to identify invalid data. The WLS method can calculate the weight value to be assigned and analyse the monitoring data. The weights are assigned as per the fluctuation degree of the monitoring data. If the fluctuation degree is still high, after multiple measurements and analysis, the assigned weights reduce; if the fluctuation degree is confined within a small range, the assigned weights enlarge (Yang and Liu, 2019).

2.3 Data collection and processing

Data processing is the key to data fusion, and data collection is the key to environmental information acquisition. The accuracy and reliability of the system algorithm are directly affected by data collection and processing (Tan et al., 2019). Data sources are divided into (1) infrared sensors, mainly responsible for detecting user location, distance detection, location determination, state determination and category. (2) Alarm and monitor, triggered by the users' abnormal state, then the data are transmitted to the system and the source is determined. (3) Light intensity sensing, temperature sensing and harmful gas sensing. Such sensors are used to perceive the physical phenomenon of the motion environment. As per the data obtained, the corresponding plan will be suggested to adjust the user's motion time and improve the motion environment. (4) Blood pressure sensing and fat monitoring record users' physical fitness data and upload them into the system. (5) Communication network and the internet, which is one of the important data sources in data fusion. The information is transmitted to the user through the internet and network system, and the real-time data are obtained through the internet for data fusion (Sun and Feng, 2020).

Data processing includes the following levels, as shown in Figure 2.

Figure 2 Data fusion level

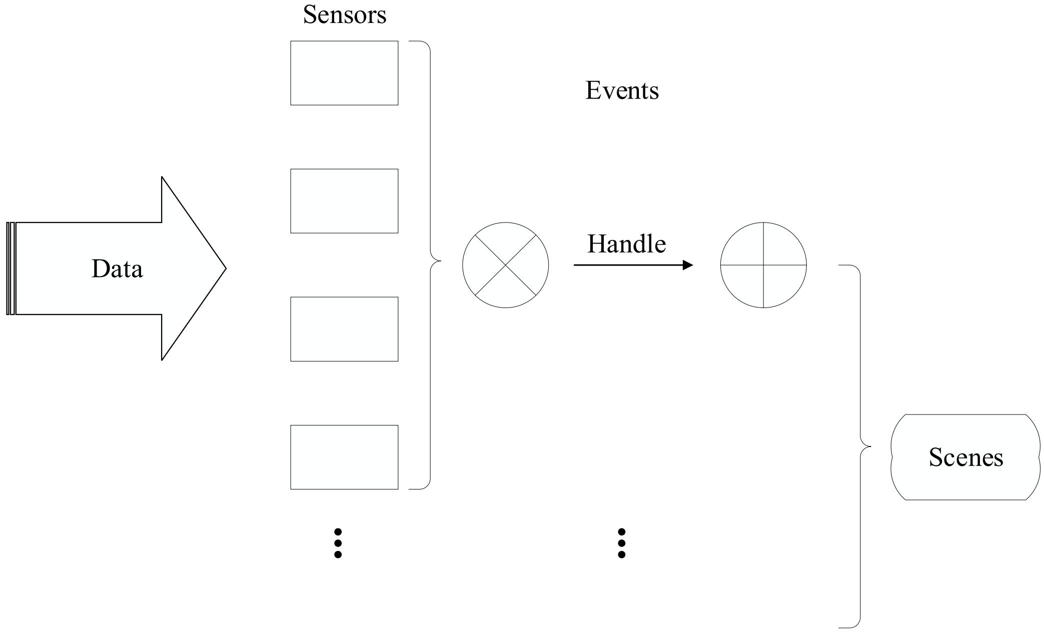


Figure 2 shows that the collected data are classified and converted; data of a single sensor are processed; sensor data in the region are fused; finally, the fusion data is analysed.

(1) *Data type conversion*: Data obtained and transmitted to the system by the sensors are only raw data, whose meaning cannot be extracted directly, inconvenient for users to identify and understand. Therefore, it is necessary to convert data into different types and assign the collected data with specific meanings that are easy to identify, such as temperature and light intensity.

Temperature conversion equation:

$$T = \frac{1.0}{a + b * \ln(\text{rthr}) + c * (\ln(\text{rthr}))^3} - 273 \tag{1}$$

In the equation, a, b, and c are constants, a=0.001307050, b=0.000214384, c=0.000000093, $rthr = \frac{(10000*(1023-x))}{x}$, and x is the real-time temperature data collected by the sensor.

Light intensity equation:

$$L = light * \left(\frac{a}{voltage}\right) \Big/ b \tag{2}$$

In the equation, a and b are constants. a=1252352, b=1023, *light* is the real-time light intensity data of the sensor, and *voltage* is the real-time voltage data.

(2) *Single data fusion*: Within the sensor-IoT, data are transmitted all the time. The load of the network system and energy consumption have increased sharply due to massive data. Moreover, the data can self-update their errors. Single data fusion is to filter and collect error data to ensure the accuracy of subsequent processing. Since the data are collected in real-time, they are independent and equal, and they can just be fused through the mean value algorithm (Li, 2019).

(3) *Regional data fusion*: After single data fusion, a set of reliable data are obtained. Currently, the sensor properties of a specific region are obtained, and the data collected by each sensor are analysed comprehensively. The sensors are independent, and their results and effect are the same, so they are averaged. Sometimes weighted fusion is needed. After the sensors in the region have been grouped, the weights are assigned according to the error analysis for fusion calculation. The weighted data fusion formula of each sensor group is obtained using the complementarity between different information and applying the maximum natural method, and the variance of the collected data is estimated to realise the weighted fusion algorithm (Lan et al., 2018).

2.4 Overall design of physical fitness system based on data fusion algorithm of IoT

The selection of multi-sensors in the data fusion algorithm varies according to different usage. A structural design of separation and fusion processing based on different sensor types is proposed. The data fusion of the same sensor type is to fuse the data measured by the same multiple parameters and calculate the parameters' correlation. When an error appears, the correlation between the sensor data can be used for correctness to ensure the data fusion precision and accuracy. Thus, even if a single sensor data gets abnormal, the whole system's function will not be affected. Comparatively, data fusion of heterogeneous sensors is to assign and fuse the data measured by different parameters (Zhang, 2020).

The region is monitored in real-time, and data are transmitted by setting sensor nodes. According to the monitoring structure and sensor type, the structural design of the system model is shown in Figure 3.

Figure 3 Data fusion model structure of the system

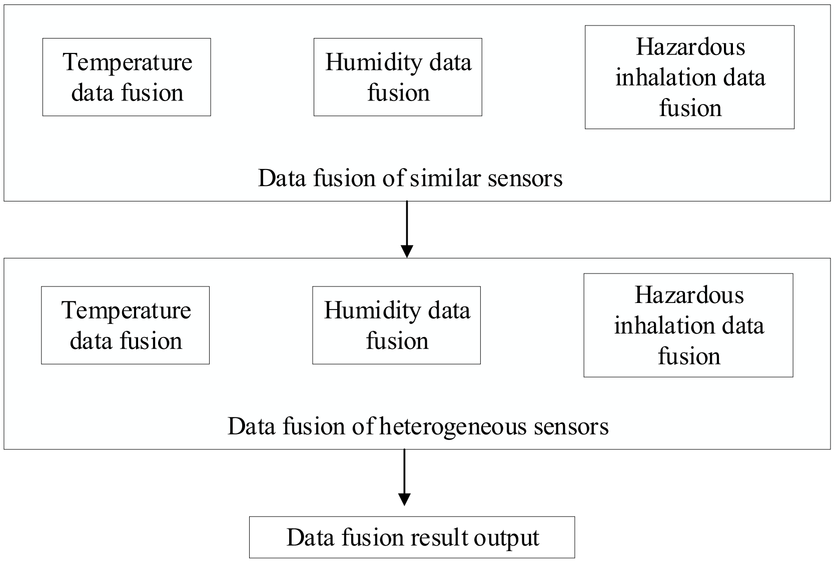
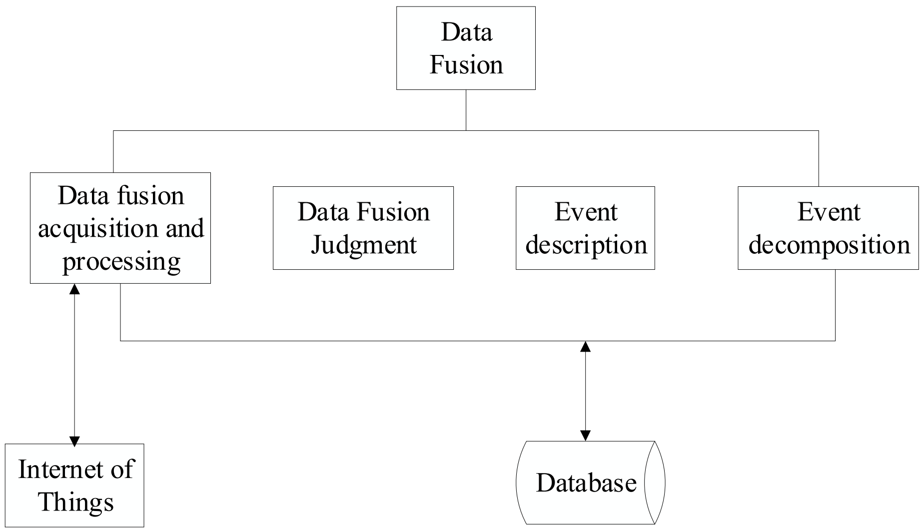


Figure 3 shows that the data fusion structure is divided into two layers. The first layer is the data fusion of the same type of sensors. The same parameters of multiple sensors are fused by the WLS method, and their correlation is analysed to reduce the influence of other factors on the fusion results and improve the reliability. The second layer is the data fusion of heterogeneous sensors, also known as decision fusion. According to the fuzzy comprehensive evaluation method, the data fusion of the first layer is comprehensively evaluated, and each parameter is assigned a weight. Thus, the results of data fusion are obtained (Liu, 2019). The established model is simulated through MATLAB, and then the programming language is exported. Finally, the storage data is analysed for operation. The software environment is configured with Windows XP Operating System (OS) and Network Simulator Version 2 (NS2). The attributes of the data fusion algorithm are simulated to test the practicability of the algorithm.

In the data fusion system, the function of the data fusion module is to collect and preprocess the real-time data obtained by the sensing equipment in the IoT for the data fusion step. The data fusion module matches the underlying data with the corresponding conditional events. Then, the event description module processes the matched events uniformly and converts the transmission form. The event decomposition module transforms events into execution instructions according to rules and transmits them to the devices. The function modules are shown in Figure 4.

Figure 4 Data fusion function module



3 Results and discussion

3.1 Communication module test results

The communication module test includes the test of the intelligent monitoring unit and the test of data transmission function between multi-sensor nodes. The simulation data of sensor node communication is obtained through hardware communication protocols and then sent by the sensors to the transceiver modules of the intelligent monitoring unit through data packages every 5 s. The module receives the data and sends it back to the data processing module for analysis and processing.

The transmission channel of the wireless communication transmission system is 11, the transmission power is 2.5 dB, the transmission baud rate is 11,520 and the PAN ID is 1,234. Concurrently, the keys are allocated to the coordinator in the intelligent monitoring unit and the terminal in the sensor node to ensure data transmission security. The stability and reliability of the wireless communication network of the system are proved by analysing data read by the serial debugging software.

3.2 Results and analysis of the data fusion algorithm and its application value

The data are chosen as the input for the mathematical model of data fusion analysis from the database and then analysed in the established data fusion model. The results are finally output to the user interface. Here, the monitored data within a random period is chosen to analyse the data fusion algorithm results, as shown in Figure 5. The monitored data of two sensor nodes are compared by the WLS fusion variance and the AM fusion variance, respectively.

Figure 5 shows that the data fusion variance of temperature WLS is between 0 and 0.02, and the variance of AM data fusion is between 1.2×10^4 and 1.6×10^4. Hence, the fusion variance of WLS is about one-millionth of AM fusion variance.

Figure 6 shows the variation of the relative humidity of 3600 s collected by two sensors simultaneously. It shows that the fusion variance of WLS measurement of relative humidity is between 0 and 0.04, while that of AM measurement is between 0 and 200. The fusion variance of WLS is one-tenth of the fusion variance of AM.

Figure 7 compares the fusion variances of WLS and AM collected by the two sensor nodes in 3600 s. The variance of WLS is between 0 and 1000, while the measurement variance of AM is between 0 and (2×10^6), and the difference between the two data fusion variances is about 1000 times.

Based on the above analysis, the WLS method for data fusion has apparent advantages and reliability over the traditional AM method, and the variance of the fusion data is only one-thousandth of that of the traditional method.

With smartphones' popularisation, their hardware and physical facilities are continuously innovated, increased, and enhanced. In terms of their software, the IoT multi-sensors are utilised to collect, fuse, process data and developed many APPs such as sports APPs. They are welcomed by the public at birth, especially those school youngsters with more free time. The more humanised human-computer interaction mode includes the ordinary fitness function and combines big data and the sensor-IoT system. Eventually, every APP user receives specific and intuitive data feedback, including their personal information and more advice and feedback for further training and the monitoring data of the sports fitness environment. Thus, sports and fitness can be exercised in a more user-friendly way.

Figure 5 Comparison of temperature variances through WLS and AM

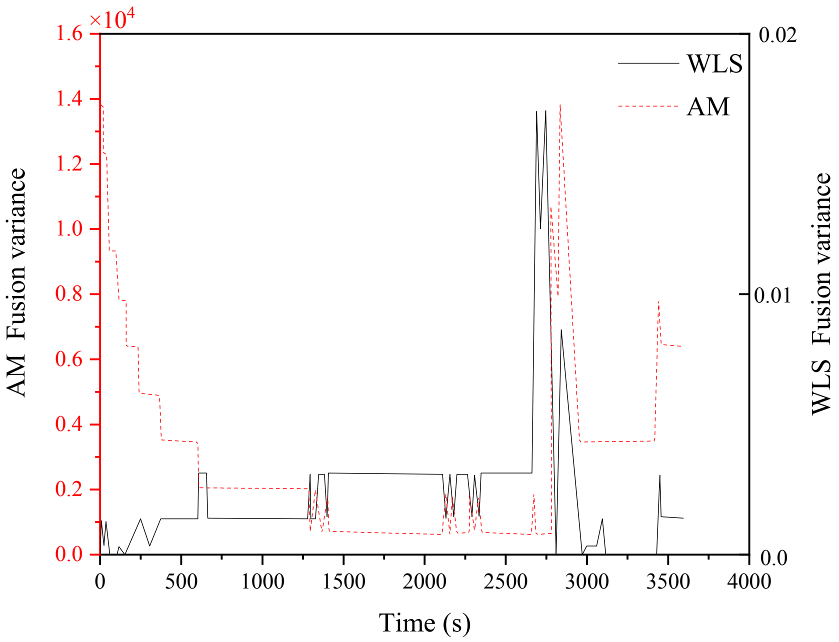


Figure 6 Comparison of relative humidity variances through WLS and AM

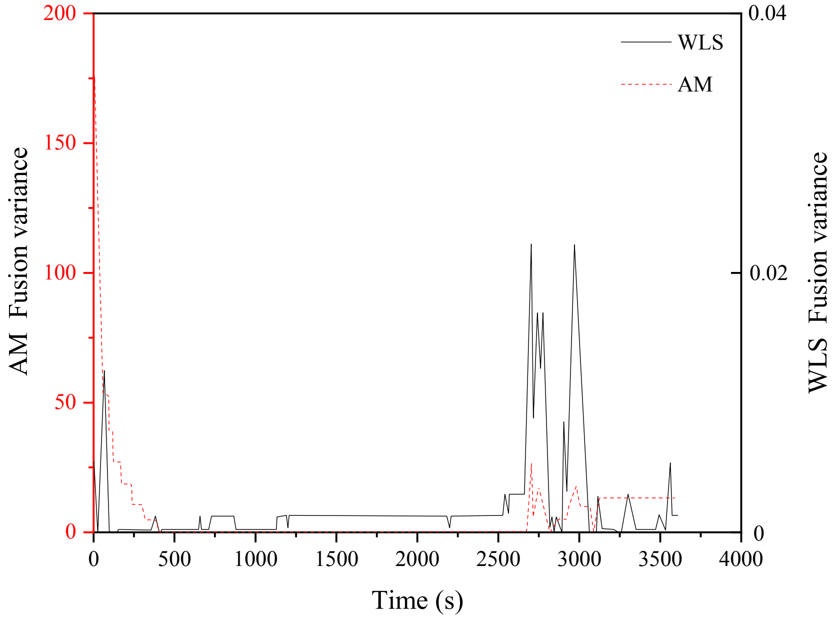
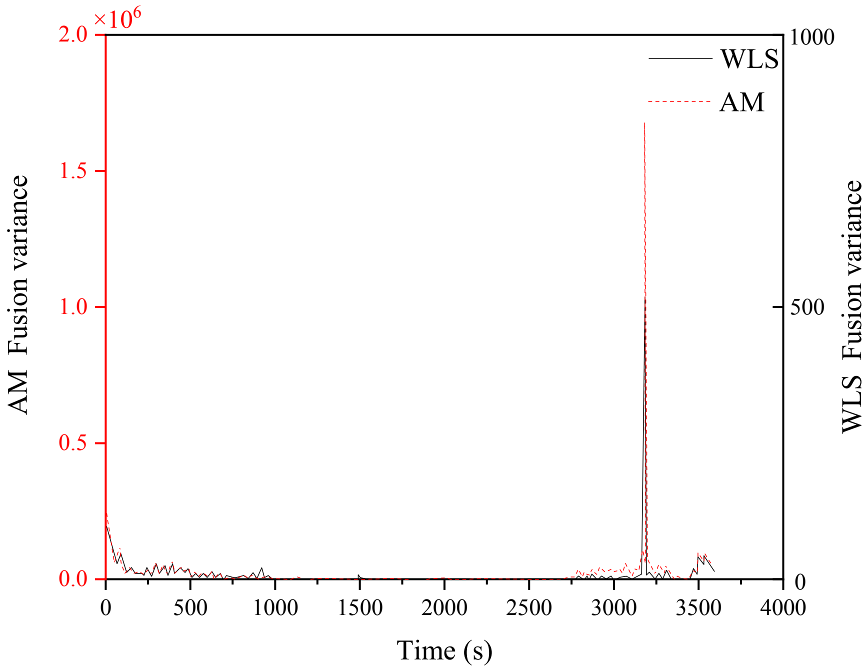


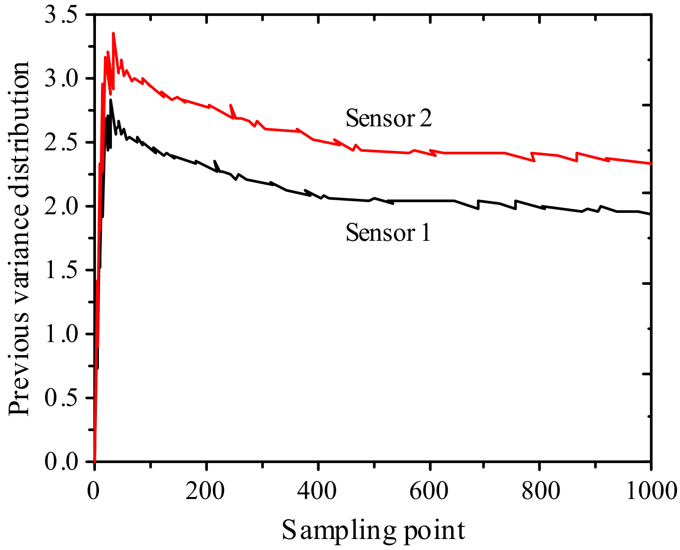
Figure 7 Comparison of variances of harmful inhalant concentrations through WLS and AM



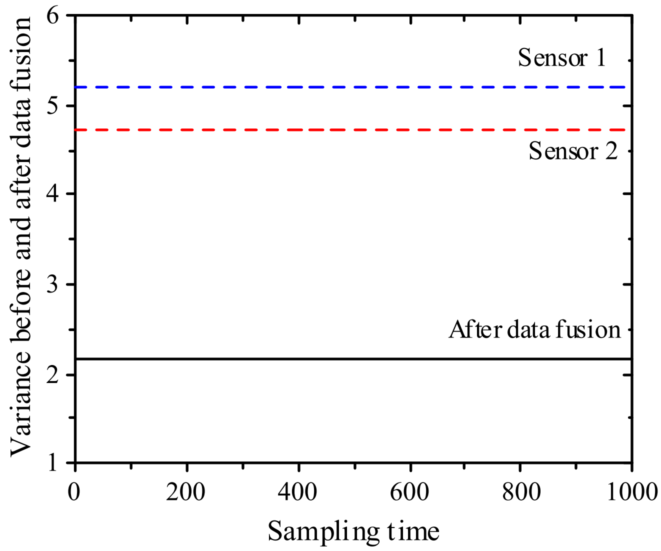
3.3 *Simulation of data fusion algorithm based on WLS*

Before the simulation, the measurement noise is assumed as follows. (a) The measurement noise of each sensor is independent white noise. (b) Since the measurement noise is caused by a variety of independent factors, such as the internal noise of the sensor and environmental interference, the probability knowledge can prove that the sum of multiple independent random variables is close to a normal distribution, and the distribution of measurement noise can be assumed to be normal. The x-axis data of each sensor are simulated through the WLS method, and the results are shown in Figure 8. Figure 8(a) shows the variance distribution comparison of two sensors, and Figure 8(b) displays the variance comparison of two sensors before and after data fusion. Through the fusion of multi-sensor measured data, WLS considers the influence of historical data and real-time data and has relatively high estimation accuracy.

Figure 8 Results of WLS simulation experiment. (a) Comparison of previous variance distribution (b) Variance comparison before and after data fusion



(a)



(b)

4 Discussion

The monitored region parameters, including temperature, humidity and harmful inhalations, are collected and perceived timely, processed, displayed in real-time and analysed periodically. The results show that the variance of data fusion of similar sensors is about one-thousandth of the AM method. The output of a heterogeneous sensor contains the membership of the regional state parameter rating. Compared with a single parameter, the data fusion of multiple sensors is more accurate and reliable. Thus, with the improved fusion algorithm, the amount of data input to the massive data fusion process reduces significantly every time, reducing redundant resources and time in the data processing process. Finally, based on the data fusion application in sports APPs, the inharmony between users and the change of the surrounding environment is solved and suggestions based on data fusion are given. The temperature, humidity, wind speed, carbon dioxide and formaldehyde in the gymnasium are monitored through the data acquisition terminals integrated with multiple sensors. The data acquired by the sensor is transmitted to the computer through a wireless network for software management, providing data for the efficient control of the sports environment. Thus, the health level of indoor participants can be improved in sports venues, providing good facilities for scientific national fitness. Next, the indoor thermal environment and air quality system should be perfected for different measurement needs.

The application results of the whole system are analysed. Compared with the traditional fusion algorithm, the improved algorithm realises more reasonable data acquisition, transmission, processing and analysis in the data fusion process. Still, the system can be further improved. The WLS method used by similar sensors can process all the original data and improve the data fusion accuracy; however, the calculation work will multiply. Therefore, the system can be further optimised to reduce the workload while ensuring accuracy. Moreover, the data acquisition parameters of sensor nodes should not be limited to the proposed test, and more items can be added to make the data fusion and later analysis of the system close to the real state.

5 Conclusion

With the development of IoT, IoT data fusion is applied in many fields. However, there are still few studies on its application in intelligent APPs. Among the emerging sports digitalisation technologies, wireless sensor technology is most critical and is widely used in real-time monitoring and data analysis for sports data. Many resources are wasted during the transmission of big data in the IoT, hindering the in-depth analysis of the data fusion system. Here, the data fusion algorithm based on the least-squares method is improved, utilising the massive data transmission characteristics in the IoT to make the final data more reliable. Eventually, the WLS method is put forward. The result proves that the wireless communication of the multi-sensor data fusion system is feasible and reliable.

Acknowledgement

This work was supported by the Academic Research Projects of Beijing Union University (No. SK60202102).

References

Chen, L. (2017) 'Technology realization of heterogeneous data fusion at sea', *Ship Science and Technology*, Vol. 39, No. 2, pp.97–99.

Dautov, R. and Distefano, S. (2017) 'Three-level hierarchical data fusion through the IoT, edge, and cloud computing', pp.1–5.

Ding, W., Jing, X. and Yan, Z. et al. (2019) 'A survey on data fusion in the internet of things: towards secure and privacy-preserving fusion', *Information Fusion*, Vol. 51, pp.129–144.

Esposito, C., Castiglione, A. and Palmieri, F. et al. (2018) 'Event-based sensor data exchange and fusion in the internet of things environments', *Journal of Parallel and Distributed Computing*, Vol. 118, pp.328–343.

Guo, J. (2020) 'Research on the application of big data and internet of things technology in extracurricular sports training and sports for young people', *Journal of Physics: Conference Series*, pp.1–6.

He, X.X., Wang, T. and Liu, W. et al. (2019) 'Measurement data fusion based on optimized weighted least-squares algorithm for multi-target tracking', *IEEE Access*, No. 99, pp.1–1.

Lan, R. Zhang, Y. and Pan, Z. et al. (2018) 'Location-dependent sensing data collection and processing mechanism in the vehicular network', *Transactions on Emerging Telecommunications Technologies*, pp.1–9.

Li, H., Liu, S.Y. and Duan, Q. et al. (2018) 'Application of multi-sensor image fusion of internet of things in image processing', *IEEE Access*, Vol. 8, No. 9, pp.1–1.

Li, Y. (2019) 'High accuracy data fusion algorithm for privacy serving in wireless sensor networks', *Journal of Intelligent and Fuzzy Systems*, Vol. 37, No. 4, pp.1–6.

Liu, S. (2017) 'Research on the application of internet of things technology in digital sports and community fitness', *Boletin Tecnico/Technical Bulletin*, Vol. 55, No. 4, pp.139–145.

Liu, Y.L. (2019) 'Research on intelligent fusion method of multisensor data in the internet of things', *Electrical Engineering and Automation*, No. 1, pp.5–8.

Nesa, N. and Banerjee, I. (2017) 'IoT-based sensor data fusion for occupancy sensing using dempster – shafer evidence theory for smart buildings', *Internet of Things Journal*, IEEE, 2017, Vol. 4, No. 5, pp.1563–1570.

Qi, J., Yang, P. and Newcombe, L. et al. (2020) 'An overview of data fusion techniques for internet of things-enabled physical activity recognition and measure', *Information Fusion*, Vol. 55, pp.269–280.

Saranya, S.S. and Fatima, D.N.S. (2020) 'Context-aware data fusion on massive IoT data in dynamic IOT analytics', *Webology*, Vol. 17, No. 2, pp.957–970.

Sun, X. and Feng, G. (2020) 'Receiving and fusion processing of space reconnaissance data based on multisensor', *Journal of Physics Conference Series*, pp.1–7.

Tan, C., Sun, Y. and Li, G. et al. (2019) 'Research on gesture recognition of smart data fusion features in the IoT', *Neural Computing and Applications*, Vol. 32, pp.16917–16929.

Torres, A.B.B., da Rocha, A.R. and da Silva, T.L.C. et al. (2020) 'Multilevel data fusion for the internet of things in smart agriculture', *Computers and Electronics in Agriculture*, Vol. 171. Doi: 10.1016/j.compag.2020.105309.

Venkatesh, V., Raj, P. and Balakrishnan, P. (2017) 'An energy-efficient fuzzy based data fusion and tree-based clustering algorithm for wireless sensor networks', Vol. 683, pp.14–27.

Yang, C.Y. and Liu, J.Y. (2019) 'Data fusion algorithm based on weighted D-S evidence theory in the internet of things', *Journal of Guilin University of Technology*, Vol. 39, No. 3, pp.731–736.

Zhang, L. (2020) 'Design of a sports culture data fusion system based on a data mining algorithm', *Personal and Ubiquitous Computing*, Vol. 24, No. 1, pp.75–86.