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Improved Particle Swarm Optimization Algorithm for Android Medical Care IOT using Modified Parameters

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Abstract This study examines wireless sensor network with real-time remote identification using the Android study of things (HCIOT) platform in community healthcare. An improved particle swarm optimization (PSO) method is proposed to efficiently enhance physiological multi-sensors data fusion measurement precision in the Internet of Things (IOT) system. Improved PSO (IPSO) includes: inertia weight factor design, shrinkage factor adjustment to allow improved PSO algorithm data fusion performance. The Android platform is employed to build multi-physiological signal processing and timely medical care of things analysis. Wireless sensor network signal transmission and Internet links allow community or family members to have timely medical care network services.

Keywords Particle swarm optimization · Data fusion · Android medical care · Internet of things · Wireless sensor network

Introduction

The Internet of Things (IOT) predicted the global information industry would be integrated into national and regional information strategy. The IOT concept was stated in 1999 by MIT's Kavin Ashton that the wisdom of rapid identification and management would come to pass. The Internet media Read-Write-Web key technologies of things involves three points: sensors, radio frequency tags and smart handheld devices (mobile phones). In the system architecture, networking consists of three dimensions: (1) sensing side: as the object recognition or sensing use, such as sensors or RFID tags. (2) Network transport layer: data transmission over the Internet to the terminal platform. (3) Applications and server: platform by the end of the attribute information for data processing, application sharing and follow-up services [1].

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IOT have a wide range of application areas, covering the need to identify and manage objects included in the application scope of things, such as environmental monitoring, transportation, medical care, industrial monitoring, public safety, agriculture, coupled with extensive wireless network coverage. The geographical scope of coverage of things will one day reach far and wide. In the past five years the world has become optimistic about medical care of things application, launching pilot projects to validate services and promotion measures. The following is a list of major development projects related to state of things: (1) United States: proposed by IBM in 2009, "Earth Wisdom Program" (Smart Earth), by U.S. President Barack Obama as a national strategy to invest 30 billion dollars in health care information technology and smart grid project. (2) Europe: i2010 policy proposed in 2009, aims to improve the wider use of economic efficiency and promote information and communications technology (ICT) development. Through the implementation of i2010, the EU hopes to enhance economic competitiveness and improve the quality of life, reduce social problems, help people build a future "intelligent environment" society. The medical applications include electronic health and medical care for an aging population. (3) Japan: 2009 Japan E-Japan and the U-Japan plan proposed based on the i-Japan 2015 program for telemedicine and electronic medical records. (4) South Korea: U-Health in 2010 to expand pilot sites with SmartCare invested 30 billion won to provide tele-medicine for chronic disease and intelligent health care services. (5)

Mainland China: In August 2009, China Premier Wen Jiabao put forward the "Experience China" concept, under the impetus of the government the networking industry has been of paramount importance. Medical applications in which the wisdom in Wuxi, Suzhou, Hangzhou, Shandong, Beijing, Chongqing, Fujian and other provinces and cities have launched a pilot used in tele-medicine, chronic health care and pharmaceuticals logistics [2].

The android medical care IOT system for multi- physiological signals fusion issues such as node signal processing, WSN localization, anti-collision and information-aggregation are often formulated as optimization subjects. This study employs improved particle swarm optimization (IPSO) to solve the convergence accuracy, convergence speed and global optimization. PSO is a swarm based intelligence optimization approach that solves optimization topics by simulating the social behavior of bird flocks. IPSO is a popular multi-physiological signals fusion for optimization technique design on the inertia weight factor and shrinkage factor adjustment. This paper uses IPSO to increase the measurement radio effect precision for multi- physiological signals fusion in android medical care IOT system computing.

The critical IOT technologies are a wireless sensor network, RFID, various sensors and embedded system. The current application of medical care IOT there are still several technical problems to be resolved: (1) dynamic network of nodes with large-scale network mobility management: When the monitoring system to a community, city or even country, its huge network and monitoring nodes and base stations have a certain mobility. Therefore, we must design an appropriate management network topology and node mobility management structure. (2) data integrity and data compression: the node can take up to 24 h of monitoring body parameters, the volume of data collected, the storage capacity is small, often using compression algorithms to reduce data storage and transmission capacity. Traditional data compression algorithms are not suitable for the high cost of sensor nodes. The compression algorithm must not damage the original data; otherwise it will result in misdiagnosis. (3) Data Security: wireless sensor network nodes form a self-organized network vulnerable to attack; in addition, the patient's information is kept confidential. Very limited computing power sensor nodes, traditional security and encryption technologies are not applicable. Therefore, the IOT system must design an algorithm for sensor nodes and multi- physiological signals fusion [3].

Literature survey

PSO is an optimization approach for global optima solution and evolutionary computation methods. This approach has been developed through a simulation of simplified social models. The features of this method are based on research on swarms such as fish schooling and bird flocking. It is based on a simple concept. It works in two steps, calculating the particle velocity and updating its position. Therefore, the computation time is short, requiring little memory. The PSO algorithm has a certain stagnation probability in a number of local minimum points. Many foreign scholars are committed to improving PSO algorithm performance. There are representative references: [4, 5] In 1998 ShiY proposed adaptive inertia factor for the particle swarm optimization algorithm.

The IOT system employs ZigBee technology to establish the measurement environment among various types of sensor nodes. ZigBee is a low cost, low power, low transmission rate, short-range wireless transmission system. It is generally defined in the IEEE 802.15.4 protocol standard, which is also on the IEEE 802.15.4 standard. It would separately define the Medium Access Control Layer (MAC) and Physical Layer (PHY) as the underlying system [6]. The IOT system based on ZigBee sensor network will be widely used in smart homes, medical care, factory monitoring, environmental control and other applications. Since 2000, many scholars have joined the ranks of those seeking to improve the PSO algorithm. Each year much literature is published in various journals on the PSO algorithm improvements. References [7, 8] are representative of this work. In 2003 Natsuki used a Gaussian variation of the proposed particle swarm optimization algorithm to improve the algorithm's ability to jump out of local convergence. In 2005 the Harbin Institute of Technology proposed a PSO algorithm based on chaotic thinking, which used a fast convergence PSO algorithm and chaotic transport ergodicity, randomness, etc., to improve the standard PSO algorithm. PSO algorithm parameters include inertia weight, acceleration factor, the convergence factor, population, etc., a large number of experimental analysis shows that these parameters for particle swarm optimization perform greatly. In different types of optimization problems PSO parameter settings are not the same. Optimization problems have different particle swarm optimization models and the model parameters may also be different. In 2005 Wuhan University of Technology XIONG Sheng Wu proposed a multi-objective optimization problem to solve the improved PSO algorithm using the PSO algorithm information transmission mechanism. The introduction of a multi-objective evolutionary algorithm, commonly used in archiving technology, using SPEA2 algorithm environment selection and matching options strategies, giving the entire group the ability to maintain an appropriate selection pressure in the Pareto optimal solution set convergence. Particles in the PSO velocity update formula, in addition to the inertia weight and acceleration factor there is a random parameter that must be adjusted [9, 10].

As rapid advances in semiconductor processing technology and embedded system technology occur, high-speed, highdensity programmable logic-element (Programmable Logic Device, PLD) are constantly being developed. These chips possess small size, low price, strong function, real-time computing, data storage applications; which makes chip design critically important. The SoC trend induces IC design companies to integrate a large number of IP into a single chip. This greatly increases the value and function of the chip. In response to this trend, domestic and international research institutions, industry and schools have introduced systematic integrated chip technology development and applications. "Biomedical Technology" is one of the key development projects in China. Many scholars at home and abroad are dedicated to biomedical engineering and biological information technology development and research. The interdisciplinary integration of multi-disciplinary research methods have migrated into medicine and social sciences technology research and development. For example, Feng Chia University developed physiological wisdom clothing; Yuan Ze University R & D developed wireless communications technology for the elderly in a home environment long-distance care system. Currently portable wireless medical monitoring technologies are the development focus. The American scholar Lewis [11] said that the future direction of medicine development will include monitoring various types of remote sensing techniques, such as video, blood pressure, medication systems, gradually replacing the costly, time-consuming clinical inquiry model. Dixie [12] pointed out that a home environment health care system, under the premise of risk-free security, patients will have the self-care ability with medical tests (such as blood glucose, ECG, blood pressure, etc.). The integration of medical and social resources into the home environment saves the elderly from the aggravating interrogation, travel time and expensive medical costs. This system also provides early detection directly from the body more efficiently at the earliest symptom stage. Simple, long-term, sustained health monitoring can be clearly recorded and transferred to a traditional clinical setting to detect deteriorating signs of diseases and physiological conditions. Internationally renowned "future people periodicals (The Futurist)" has shown a significant change by predicting the future of human life through technology products, "the family with the health monitoring system (Home health monitors)" will become mainstream. The IOT system monitoring your bowel, liver function, hormones, etc., as simple as the amount of weight at home, by analyzing your breathing, urinating, etc. The IOT system will be able to give you basic health information [13].

Android IOT system architecture and development platform

Figure 1 illustrates the scope of this study, physiological signal processing of multi-source Android remote medical care system, called the HCIOT system. Our research includes: analysis of physiological signals and measurement; the Android platform using FPGA design computing physiological signal processing unit; collection of information signals to extract accurate physiological signals; RFID identification system; ZigBee wireless module able to return physiological signals to the database and network PC. Multi-source sensor data fusion is accomplished based on multi-sensor collection and analysis processing module. RFID and ZigBee technology is used to build a remote medical care system for wireless network research. This system can be used in hospitals to collect personal data to monitor the physical health care information systems. The Institute developed RFID and ZigBee wireless sensor network systems technology to help medical institutions and organizations with their employee medical care and physical data consolidation [14, 15].

The system can be used in hospitals to monitor users from a simple standard instrument. This allows the hospital to reduce the medical manpower burden, reduce the workload on medical staff and increase efficiency. Personal care home users can perform their own self-health check. In long term care facilities and elderly care center organizations the control center can monitor the patient's body. If companies have improved self-care health examination equipment, the staff will be able to understand the warning and respond accordingly. This will reduce deaths from staff overwork and chronic diseases such as cardiovascular disease. RFID is used to confirm patient identity. This will reduce to incidence of wrong medicine being administered to patients, reducing medical negligence and strengthening drug control. The system uses the standard physiological measurement equipment and measuring instruments to measure blood pressure, blood oxygen, heart rate, body weight and body fat. A weight and body measurement is the mean patient values.

The Criticare 506DXN2 system is a physiological monitor, (as shown in Fig. 2), used to measure blood oxygen (SpO2), heart rate and non-invasive blood pressure (NIBP) measurement. Heart rate measurements are determined by the volume change. Without oxygen, such as timing, the heart rate is measured using the blood pressure data display. Criticare 506DXN2 optional type system provides internal thermal printer 506DXNP2 model, with a temperature gauge 560DXT2 and printer 506XNTP2.

In this study, physiological measurement system to measure the user's physiological signals, and further was do remote monitoring system for this study in Fig. 3 flow chart. Users first use RFID for identity recognition, and then perform the physiological signal measurements. This system has the following types of physiological signal measurements, body weight, body fat, blood pressure, blood oxygen and heart rate. ZigBee is used to send and receive the

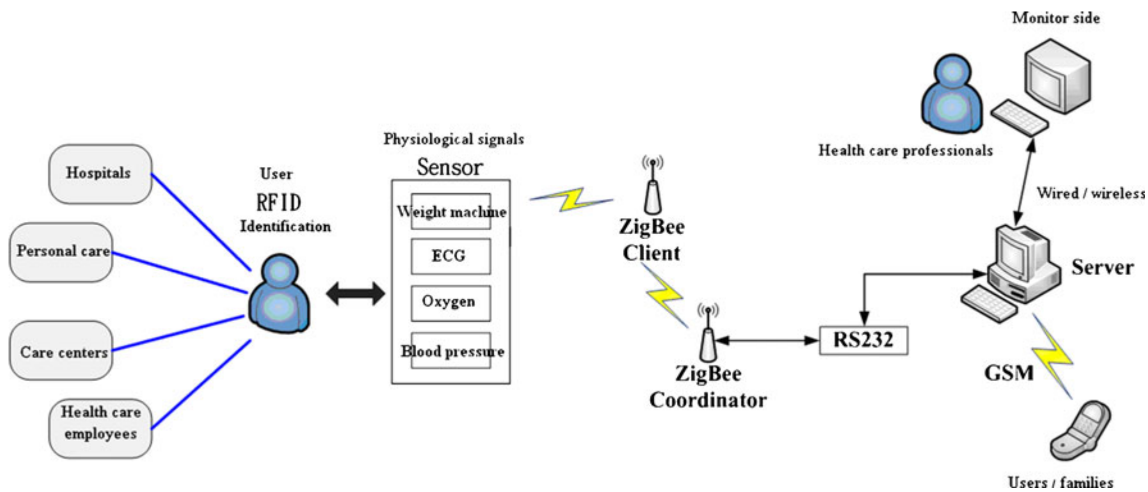


Fig. 1 Physiological signal processing as much as the Android source telemedicine care system diagram (HCIOT) in this study

measurement data. This system is standard medical equipment. The measurement results are accurate, provide a doctor or hospital with prolonged disease tracking and observation [16, 17].

Improved PSO Algorithm

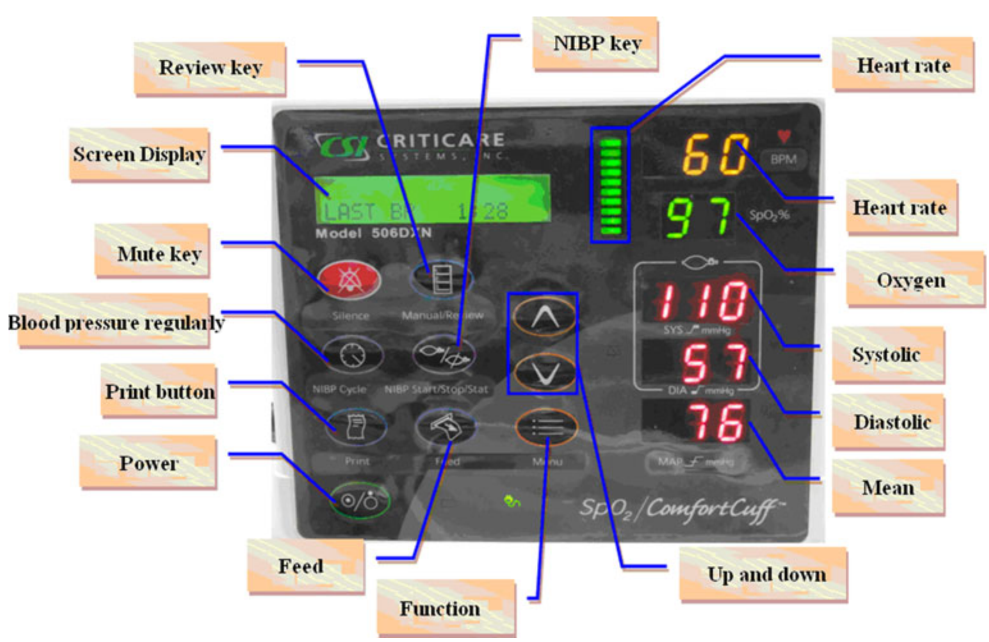
Data aggregation in the multi-physiological signal fusion system is based on a common source. Certain allocation strategies will be grouped into multi-sensor observations. This paper proposes an improved PSO (IPSO) algorithm to solve multi-dimensional distribution. The multi-objective expression data association problem for a class of combinatorial optimization problems to solve constraints is confirmed using a measurement sensor [18]. Assume the search space is n-dimensional, particle swarm particle velocity in the i-th position of $x_i(x_{i1}, x_{i2}, \ldots, x_{in})$, the speed of the i-th particle is expressed as $v_i(v_{i1}, v_{i2}, \ldots, v_{in})$, The i-th particle so far the best search position is expressed as $pbest_i(p_{i1}, p_{i2}, \ldots, p_{in})$, the particle swarm so far search the best position so far recorded as $gbest_i(g_{i1}, g_{i2}, \ldots, g_{in})$. The next generation of particle positions and velocity according to Eqs. (1) (2) is updated using:

$$v_i(t+1) = v_i(t) \cdot \omega + c_1 \cdot Rand_1 \cdot (pbest_i - x_i(t)) + c_2 \cdot Rand_2 \cdot (gbest_i - x_i(t)) \quad (1)$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \quad (2)$$

In the above formula; t represents the current generation t-th iteration, acceleration constant c_1, c_2 are two non-

Fig. 2 Criticare 506DXN2



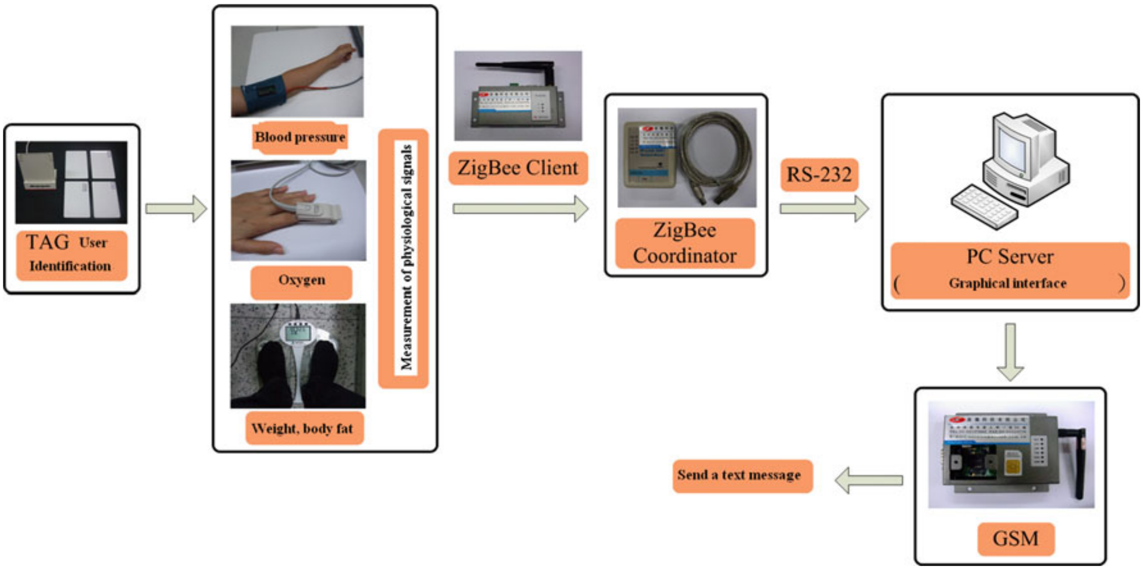


Fig. 3 Flow measurement system operation

negative, $Rand_1$, $Rand_2$ are uniformly distributed random number between[0 and 1]. To make the particle velocity not too large this study set the speed limit at v_{max}, that is, when Eq. (1) is$|v_{id}| > v_{max}$, to take$|v_{id}| = v_{max}$. This ω is the inertia weight which determines the particle speed prior to the current velocity and thus functions as a balancing algorithm global search and local search capacities. Large inertia weight enables the IPSO algorithm to have better global search ability and fast convergence speed, but the accuracy is not high. A smaller inertia weight gives the search algorithm higher accuracy, but the convergence is too slow. The inertia weight factor can be calculated to improve IPSO algorithm performance.

The basic particle swarm algorithm Eq. (1) is rewritten as (3):

$$v_i(t+1) = G_1 + G_2 + G_3 \tag{3}$$

Where

$$\begin{aligned} G_1 &= v_i(t) \\ G_2 &= c_1 \cdot Rand_1(pbest_i - x_i(t)) \\ G_3 &= c_2 \cdot Rand_2(gbest_i - x_i(t)) \end{aligned} \tag{4}$$

The speed of entry for the originalG_1, G_2, G_3 said the amendment to the original speed, which $G_2$is the best position to consider the particle impact history on the current position, and G_3 is the best position to consider the particle group history, the impact on the current position, first type (3) to modify:

$$v_i(t+1) = G_1 \tag{5}$$

Particles speed will remain unchanged at this time, flying along the direction of the border until it makes the particles difficult to search optimal solution. Equation (3) is then used to modify:

$$v_i(t+1) = G_2 + G_3 \tag{6}$$

Particle speed will depend on the optimal location at its history and the history of the optimal location of groups, resulting in the speed non-memory. The basic particle swarm algorithm has a global search capability, which shows the particle velocity equation G_1item evolution, used to ensure the global search algorithm has a certain capacity, G_2, G_3 give the IPSO algorithm local convergence.

Determining the local search ability and the ratio between the global search capability for the solution process is very important, so YuhuiShi proposed improvements with the inertia weight particle algorithm. Some literature suggested that when the inertia weight range is ω = [0.8, 1.2] the algorithm converges the fastest. However, when $\omega > 1.2$ the results will fall faster into local minima. Inertia weight ω is similar to simulated annealing in temperature. A larger ω has better global convergence, while a smaller of ω has strong local convergence. As the number of iterations increases, the inertia weight ω should continue to decrease, thus making the particle swarm algorithm in the early stages have strong global convergence. The latter has strong local convergence. This study will satisfy the equation ω correction (7):

$$\omega(t) = 0.9 - 0.5 \times \frac{t}{MaxNumber} \tag{7}$$

Where the MaxNumber is the maximum number of iterations, so that the inertia weight ω can be viewed as a function of the number of iterations and can be from 0.9 to 0.4 . The study also introduces decreasing index and iteration threshold particles swarm optimization algorithm for linear decreasing weighting strategy to improve the optimization process, the inertia weight with the current iteration, the index rate and decreasing the threshold value of non-linear iterative of change, that:

$$\omega(t) = \left(\frac{t-1}{T-1}\right)^{\lambda}(\omega_f - \omega_i) + \omega_i \tag{8}$$

Where λ is a decreasing index; T is the iteration threshold; ω_i is the inertia weight of the initial value; ω_f is the inertia weight value when the iterations are to reach the threshold value. When the number of iterations are t to T,$\omega(t) = \omega_f$, and the search ends. Throughout the iterative process, because the introduction of λ, $\omega(t)$ increases with the number of iterations in a nonlinear decrement, the local extreme points are helped. The early iterations that the $\omega$is larger particles and faster flight speed over the entire search space to determine the approximate range of the optimal value, with the iteration forward and the ω non-linear decrease, the majority of particles gradually reduces the search range and concentrate in the neighborhood of the optimal value range. The iteration threshold value is reached at the end, the inertia weight is limited to ω_f, and particles with almost the same flight speed in the neighborhood of the optimal value to improve the convergence speed.

Experimental Simulation and Result Analysis

This study employed the Android platform for a family community health care of things. The IOT system employed the RFID and ZigBee wireless sensor network technology to build a remote medical care system. a sensor network of nodes is used to collect and process the physiological signals and analyze the results through ZigBee wireless devices. The users will be able to use smart phones to make medical queries. Because a variety of home users use a variety of physical devices with RS-232/485 serial communications interface, this study will be based on this interface. This will allow home users to set up the system in the existing environment. Wireless sensor networks can monitor a variety of physiological signals, such as blood pressure sensors, ECG monitoring, pulse and temperature. The Android computing management platform combines database systems allowing remote supervision and management. Although sensor data fusion research has been quite extensive, but the basic theoretical framework and an effective generalized model and algorithm fusion problem has not been solved. Still, researchers have made many more mature and effective integration algorithms. The measurement sensor is usually assumed that a statistical model includes independent additive Gaussian noise statistics and the sensor measurement errors are independent. In this study, using the Android platform a family community health care of things, the multiple physiological signals weighted average method is used, which is one of the most simple and intuitive multiple sensor methods providing redundant information. This method can deal with dynamic real-time raw data, but the determination of weights has a certain subjectivity. For example, a test target for detection of N times, the average $\overline{x}$ is:

$$\overline{x} = \frac{\sum_{i=1}^{N} k_i x_i}{\sum_{i=1}^{N} k_i} \tag{9}$$

kj is assigned to the i-th test weights [19].

In the IOT, the data integration step are very important role, mainly in the energy of the entire network to enhance the accuracy of the information collected and gather information to improve the efficiency and so on. Nodes in the same region of the information collected with great redundancy in the net for information integration, to a certain extent, the overall Internet data collection efficiency is improved. Using local computation and raw data integration in multi-hop data transmission to a certain level of treatment,

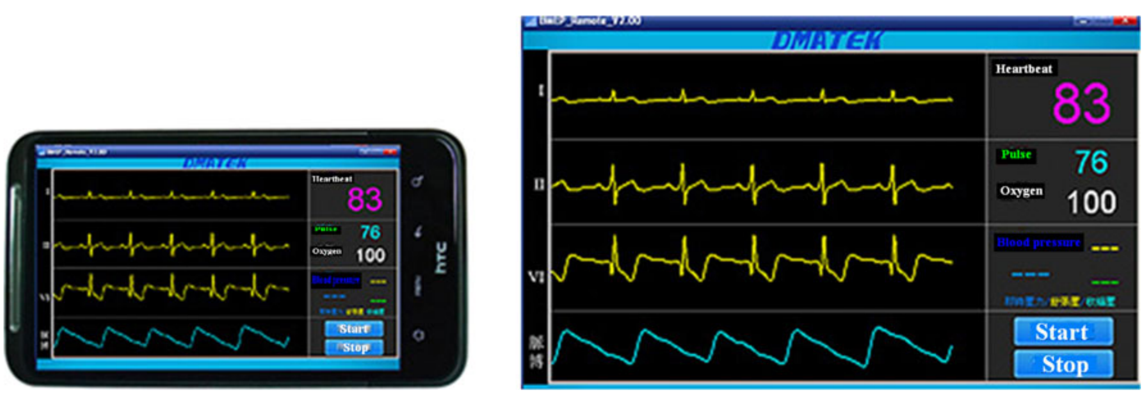


Fig. 4 Schematic diagram of the remote control handset

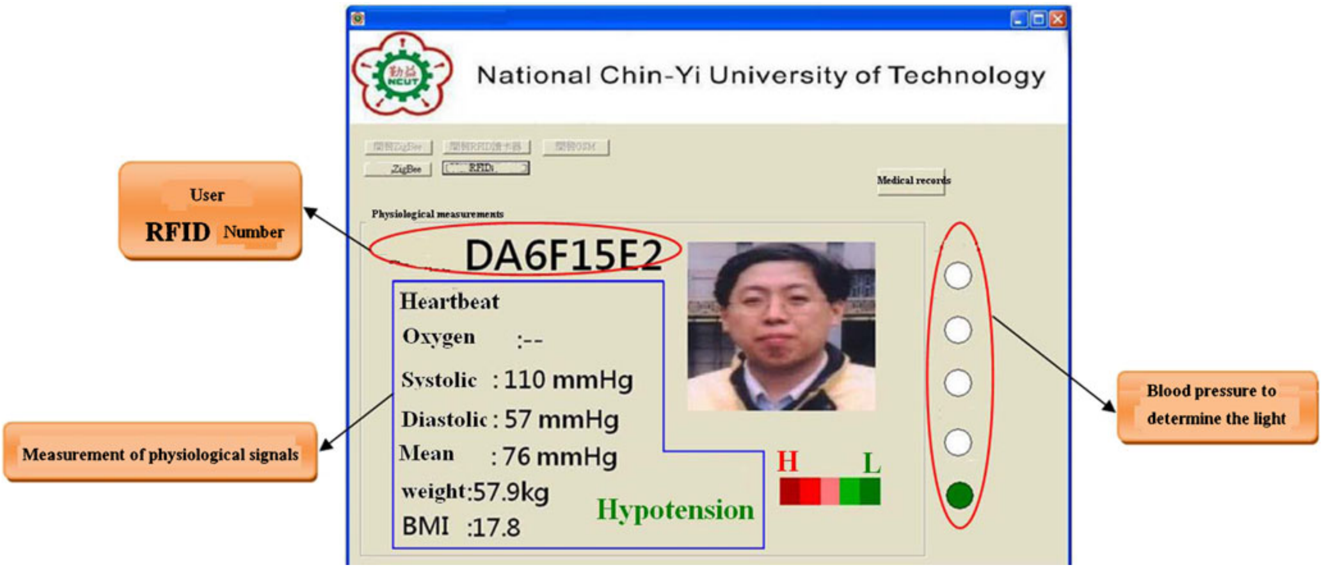


Fig. 5 Schematic diagram of the system measurements

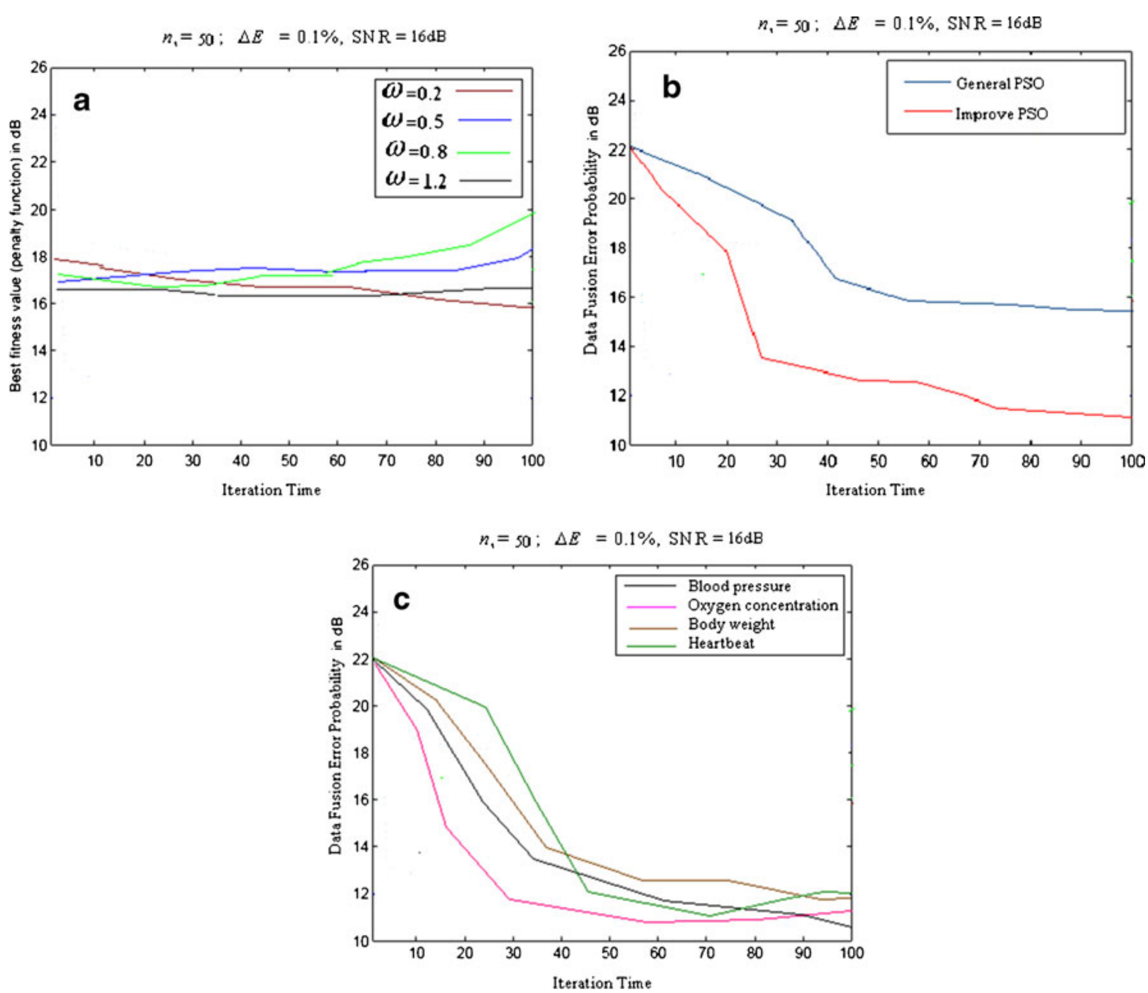


Fig. 6 Multiple physiological signal fusion function convergence based on improved PSO: multi-sensor data fusion error probability is below 0.1 % **a**. Best fitness returned for improved PSO iterations for a given ω parameter. **b**. Comparison the general PSO with improved PSO in data fusion error probability. **c** Improve PSO when various medical behaviors in error probability. (n_s= 50; ΔE = 0.1 %, SNR=16 dB)

only to send useful information, reducing the need to transfer the amount of data, can reduce the transmission network congestion and reduce the data transmission delay. Even if effective the amount of data is not reduced. By merging multiple data packets to reduce the number of data packets, the transmission collision conflicts can be reduced, improving wireless channel utilization.

Figure 4 shows the body measured by physiological signals. The developed measurement system intercepts the initial electro-physiological analog signals because such a relatively weak signal is subject to noise interference. The FPGA is used to design signal processing related to the DAC circuits. After signal conversion we designed a finite pulse response filter (FIR Filter) to rebuild to the system as a follow-up treatment. The system start-up based on RFID-based wireless identification by caregivers through a bracelet on the TAG chip to communicate with the cloud platform. We also synchronized the image transfer so that the patient can be viewed. In addition to the portable system design features to suit local conditions the signal can be transmitted over the wireless network to monitor the host for further diagnosis. Android phones can be used with local biomedical platform RS232 ZigBee CC2530, BT via WiFi, 3 G wireless Internet access (Figs. 5 and 6).

The proposed IPSO performance was evaluated using the basic PSO for comparison. The parameter x is recommended by Shi and Eberhart [20] with a linearly decrease which changes from 0.3 to 0.8. The acceleration constant c_1, c_2 is both 1.8. This $x_{\max}$ and $v_{\max}$ are set equal. In our case the following values are used as default: p=4; m=2q, where p is the number of sub-swarms, m is the number of points in each sub-swarm, q is the particle population size selected from the points in the sub-swarm. The ZigBee CC2530 chip with RFID for IOT was used for the experimental simulation. The program was compiled using IAR Embedded Workbench software and then coded. Development board through the JTAG Debugger multi emulator interface to USB interface connected to the computer. The code was then burned to each sensor node's battery plate and sensing element according to the type of node burned with the appropriate code. The experimental simulation environment is the general home environment.

In the IOT system experimental analysis, $n_s$equal 50 was used as the number of multiple wireless sensors, the ω parameter between 0.5 to 0.8 is the most suitable for the operation of the system performance. When using the improved PSO 20 to 30 iterations were used to obtain the first system improvement. The situation becomes more obvious from the final integration of physiological signals that the oxygen concentration measurement status is a relatively small error condition. It is relatively stable because the oxygen measurements is the heartbeat measurement project, which is a more difficult measurement.

Conclusions and Future Work

This study presented various types of physiological measurements through the ZigBee technology to establish a wireless physiological health care system. We applied this system to monitoring the human body. Long-term trace detection of the body itself is possible for monitoring common health problems. This system allows users to better understand their physical condition, providing early detection by the hospital for further treatment. The IOT system uses ZigBee wireless sensor network technology combined with RFID technology to monitor the status of a given healthcare region. This paper proposed better IOT system improved issues than the traditional optimal solution. The general PSO multi-sensor data fusion computing error probability is below 0.1 %. This improved PSO IOT system is effective due to its simplicity, high solution quality, fast convergence and insignificant computational burden, better than existing PSO approaches. The iterative nature of the improved PSO can be used in high-speed real-time applications, especially if optimization needs to be carried out frequently.

The proposed system can be applied to employees in the technology industry for body health check. In accordance with each patient monitored, a more simple and rapid method of medical early warning function is contained, so that medical resources can be used more appropriately to avoid waste. In the future real-time data processing and analysis of the results transmitted by the wireless network system to the medical center will be possible. Physical measuring instruments for conditions such as diabetes, cholesterol, liver function monitoring can be added so that users can get more health information.

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References

1. van den Bergh, F., and Engelbrecht, A. P., A cooperative approach to particle swarm optimization. *IEEE Trans Evol Comput* 8 (3):225–239, 2004.
2. P.K. Tripathi, S. Bandyopadhyay, S.K. Pal, Multi-objective particle swarm optimization with time variant inertia and acceleration coefficients, Information Sciences 177 (22) (2007) 5033–5049.
3. R. Mendes, J. Kennedy, J. Neves, The fully informed particle swarm: simpler, maybe better, IEEE Transactions on Evolutionary Computation 8 (3) (2004)204–210.
4. C.C. Lai, C.H. Wu, M.C. Tsai, Feature selection using particle swarm optimization with application in spam filtering, International Journal of Innovative Computing, Information and Control 5 (2) (2009) 423–432.

5. N.K. Khalid, Z. Ibrahim, T.B. Kurniawan, M. Khalid, N.H. Sarmin, Function minimization in DNA sequence design based on continuous particle swarm optimization, ICIC Express Letters 3 (1) (2009) 27–32.
6. A. Carlisle, G. Dozier, An off-the-shelf PSO, in: Proceedings of the Workshop on Particle Swarm Optimization, Indianapolis, IN: Purdue School of Eng. Technol., IUPUI, April 2001.
7. H. Wang, H. Li, Y. Liu, et al., Opposition-based particle swarm algorithm with Cauchy mutation, in: Proceedings of the 2007 IEEE Congress on Evolutionary Computation, September 2007, pp. 4750–4756.
8. D. Bratton, T. Blackwell, A Simplified Recombinant PSO, Journal of Artificial Evolution and Applications, 2008.
9. Richer, T. J., Blackwell, T. M, The Levy particle swarm, in: Proceedings of 2006 IEEE Congress on Evolutionary Computation, Vancouver, Canada, 2006, pp.808–815.
10. Kennedy, J., In search of the essential particle swarm, in: Proceedings of 2006 IEEE Congress on Evolutionary Computation, Vancouver, BC Canada, July 2006, pp. 1694–1701
11. A. Ratnaweera, S.K. Halgamuge, H.C. Watson, Self-organizing hierarchical particle swarm optimizer with time-varying acceleration coefficients, IEEE Transactions on Energy Conversion 8 (2004) 240–255.
12. Ni, Q. J., Xing, H. C., An improved Gaussian dynamic particle swarm optimization algorithm, in: Proceedings of 2006 International Conference on Computational Intelligence and Security, Guangzhou, PR China, November 2006, pp. 316–319
13. Bratton, D., Kennedy, J., Defining a standard for particle swarm optimization, in: proceedings of 2007 IEEE Swarm Intelligence Symposium, 2007, pp.120–127.
14. Sung, W.-T., Chung, H.-Y., Design an Innovative Localization Engines into WSN via ZigBee and SOC", 2008 CACS International Automatic Control Conference,Nov.21~23 2008
15. Sung, W.-T., Determine Global Energy Minimum Solution via Lyapunov Stability Theorem", International Journal of Innovative Computing, Information and Control (IJICIC), Vol.5, No.7,pp.1-08-22.July 2009
16. Higashi, N., Iba, H., Particle swarm optimization with Gaussian mutation, Proceedings of the IEEE Swarm Intelligence Symposium 2003, Indianapolis, Indiana, USA (2003) 72–79.
17. X. Zhao, A perturbed particle swarm algorithm for numerical optimization, Applied Soft Computing 10 (1) (2010) 119–124.
18. Y. Liu, Z. Qin, Z. Shi, J. Lu, Center particle swarm optimization, Neurocomputing 70 (4–6) (2007) 672–679.
19. Shi, X., Lu, Y., Zhou, C., Lee, H., Lin, W., Liang, Y., Hybrid evolutionary algorithms based on PSO and GA, Proceedings of IEEE Congress on Evolutionary Computation 2003, Canbella, Australia (2003) 2393–2399.
20. O. Montiel, O. Castillo, P. Melin, A.R. Daz, R. Seplveda, Human evolutionary model: a new approach to optimization, Information Sciences 177 (October) (2006) 2075–2098.