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AGENT-BASED PULSE WAVE IDENTIFICATION METHOD FOR IOT HEALTHCARE SYSTEM

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Abstract. This paper presents a real time pulse wave identification method based on a multi-agent system. Medical IoT (Internet-of-things) systems are rather restricted in terms of resource consumption and processing time, especially in emergency situations, thus decision making processes must comply real-time requirements. This research mainly focuses on assistive healthcare domain. The environment is treated as IoT network with proactive sensing, actuation and decision support capabilities. Multi-agent systems are proposed as a useful binding technology, encapsulating IoT and healthcare domains as well as serving as an engineering technique for this class of proactive time-critical systems. As an experiment, the proposed agent-based IoT healthcare systems' development method was applied for pulse wave identification. The results have proved that agent technology is beneficial in IoT healthcare domain in terms of processing time, capable of achieving real time decision making in emergent situations.

Key words: Internet of Things (IoT), healthcare, multi-agent systems, pulse wave identification, real-time processing, Photoplethysmography (PPG).

1. INTRODUCTION

1.1. Healthcare and IoT domain

The growing population of elderly people is putting high demand on healthcare sector, strengthening the cognition that disease prevention is as important as cure. Continuous technological progress opens up broad prospects for modern healthcare systems, paving the way from traditional to digital patient. Though still in its infancy, IoT-based remote health monitoring is becoming an increasingly viable solution for healthcare provisioning in the near future [1]. Healthcare intellectualization as well as IoT adoption processes are driven by state-of-the-art sensing technologies, giving an alternative to choose from wearable, remote or even implantable devices. The miniaturization of wearable non-invasive medical systems ensure the monitoring of human physiological parameters such as heart-rate, respiratory-rate, skin conductance or muscle current and allows not only the identification of human activity, state, sleep patterns, critical diseases but even the recognition of human emotions. These medical gadgets, often called "wearables" are usually rich in features, provide real-time feedback, important alerts and ensure direct access to personal analytics, thus empowering self-monitoring and individual care away from hospitals. Furthermore, with the expansion of the Internet of Things, the data collected by wearable medical gadgets can be transmitted to healthcare provider systems to assist the treatment process, as well as used for deeper analysis, decision making processes and diagnostics revealing the possible insights into health risk.

Contemporary IoT systems, by its nature, combine off-the-shelf sensor technologies, communication standards, cloud computing or even machine learning as a service into one place. From this point of view, modern e-health monitoring system is a complex interconnected structure with distributed architecture, where promising benefits meet significant challenges, associated with each of its components. Simple and secure connectivity, power consumption, security risks associated with sensitive medical data, as well as the importance of sensor measurements' accuracy in emergent situations are commonly cited issues or so called "bottlenecks" for medical IoT [1,2]. IoT yields high-impact problems that require solutions that go beyond traditional ways of thinking [3] thus IoT research community is actively involved in seeking for new and approved solutions in this field [4,5].

1.2. The potential of multi-agent systems

For the last two decades agent-based technology have been acknowledged and widely used as a solution for engineering various ambient intelligence systems [6] with widespread application domains ranging from smart homes [7] to cloud manufacturing [8], cybersecurity [9] and many others. In the domain of Ambient Assisted Living, MAS (multi-agent systems) has recently been marked as the most used paradigm [10]. Extensive characteristics of agent systems such as autonomy, intelligence, adaptability, proactivity, integration and cooperation as well as latest research in [11,12,13] confirm that agent systems are closely related to IoT domain and at the same time are said to represent the most promising information technology for coping with a class of problems in healthcare [14]. The abundance of MAS research and cited beneficial properties allows considering MAS a useful binding technology, encapsulating IoT and healthcare domains as well as serving as an engineering technique for this class of proactive time-critical systems.

Resource consumption is a considerable issue in IoT systems, because most of IoT nodes rely on batteries. Health monitoring involves continuous sensing and wireless data transmission, which severely limits the battery life of wearable IoTs. Frequent battery recharging or replacement stands as the major impediment to the ultimate vision of fully autonomous healthcare [5], thus we offer modelling IoT systems as agent-based systems. The agents in the system can abstract IoT devices, act as mediators for delivering and processing IoT content, thus preserving physical IoT nodes from wasting resources through sustained communication with end clients. Agent themselves can enter a sleeping mode or can be even deleted after the execution of some function. Another beneficial agent feature is their mobility, which means that agents can migrate from one node to another and accomplish some required task only when necessary. Event triggered behavior also contributes to ensuring energy efficiency issues, as the system puts itself to the idle state whenever possible. Furthermore, IoT healthcare system must be addressed as an ever evolving system, which might require scalability, modularity and dynamic reconfiguration at run-time. Agent systems are can change their appearance, new agents can be added to the system when needed. In case of information overload, new agents can be created and data processing can be divided between several agents, seeking the optimum balance in traffic load.

1.3. Pulse wave identification problem

The accuracy of sensor readings as well as real-time processing and effective decision making are one of the aforementioned challenges in medical IoT. Real-time pulse wave identification problem is presented in this paper as an experiment to illustrate the adoption of the proposed agent-based method. Pulse is one of the most important human vital signs. Detection and interpretation of pulse wave is an important technique in examining human health, for assessing arterial stiffness, calculating heart rate, detecting diseases or other human pathological changes. Motivated by unmet needs in low cost, non-intrusive and portable techniques in healthcare, the photoplethysmography (PPG) technique has been extensively researched in the later decades. Due to technological advances in the field of opto-electronics, clinical instrumentation and digital signal processing, the PPG technique achieved a broader spectrum of potential applications, ranging from the field of clinical physiological monitoring to the vascular assessment, autonomic function evaluation [15] and even in post-surgical treatment and recovery [16].

Photoplethysmography is based on small, wearable pulse rate sensors. These devices, consisting of infrared light-emitting diodes and photodetectors, offer a simple, reliable, low-cost means for monitoring the pulse rate noninvasively [17]. PPG uses a light source and a photodetector at the surface of skin to measure the volumetric variations of blood circulation [18]. Generally PPG recordings are performed at peripheral sites on the body, such as fingers, ears, toes, neck, forehead, or wrist and even foot. During pulse wave analysis it is important to extract significant points such as systolic peaks, onsets, and dicrotic notches from PPG waveforms accurately [19]. However, the systolic and diastolic waveforms of pulse wave change due to various factors such as the characteristics of blood vessel wall, blood viscosity, proper vibration of tissue in the artery system, and others [20]. This means that pulse waveform shape, often called the contour or the morphology of the waveform, would vary between human, having different habits, weight, diseases or age. This verifies the statement in [21], that each human individual has a specific pulse wave signature. The identification of the individual pulse waveform is important as it can serve as a reference template in pulse wave detection process.

Data collected by wearable sensors is easily influenced by motion artifacts and other bioelectrical signals that may complicate the detection of the cardiac component, significantly distort the data and degrade the quality of analyses performed on the data if not identified and removed [22]. Pulse waveform can be influenced by a variety of effects such as technical artifacts, arising from physical equipment itself, environmental artifacts – arising from outside the patient as well as biological artifacts, caused by patient movement, or even cough [23]. Artifacts are the most common cause of false alarms, loss of signal, and inaccurate measurement in clinical monitoring [23] and are difficult to filter because they do not have a predetermined frequency band and their spectrum often overlaps with that of the PPG signal. Furthermore, type, incidence, duration, and severity of motion artifacts varies significantly between different environments and patient populations [24].

The reduction, or at least minimization of noise in PPG signals is very important, however a challenging task and this is witnessed by the intensity of research in this area during last decade. The authors have investigated various methods [25] ranging from conventional signal processing techniques, such as independent component analysis, correlation, wavelet-based methods, various filtering techniques to various statistical approaches. Artificial intelligence techniques such as Bayesian Networks [26], ANN [21] or support vector machines [27] have also been reported to be useful in motion artifact reduction in photoplethysmography. The reviewed pulse wave identification methods typically declare high accuracy and precision, however most of them are performed in stable experimental setup, with high computing power, but not in the restricted IoT context. Thus, in this paper we adopt pulse wave identification method presented in [28] and realize the decision logic in real-time IoT environment. Furthermore, the obtained experimental results lead to conclusion that algorithm decomposition, i.e. the distribution of processing and decision making to separate agents is beneficial in IoT domain in terms of computational time and power consumption.

2. AGENT-BASED PULSE WAVE IDENTIFICATION METHOD

This research mainly focuses on assistive healthcare and continuous patient monitoring at home or hospital environment, or, in a broader context – Ambient Assistive Living problem domain. The environment is treated as IoT network with proactive sensing, actuation and decision support capabilities.

This section presents an agent-based pulse wave identification method. First, the generic agent-based IoT healthcare systems' architecture is proposed to reveal the basic components of the problem domain and then the algorithm for pulse wave identification is described.

2.1. IoT healthcare system architecture

The adoption of agent technology lays the essential system development principles – systems are designed and implemented as a group of autonomous, collaborative and proactive components, each having dedicated sensing, actuation, processing or control functions.

Fig. 1 presents the reference architecture of agent-based IoT healthcare system, composed by two main parts – virtual and physical environments. All software agents in the system can be distinguished as marked with letter A. Physical system components, i.e. sensors, actuators and the users are depicted at the lowest part of the physical environment. The users, denoted in the picture, stand for the general representation of system users, both doctors and patients. Physical sensors indicate any sensors, measuring various physiological parameters (pulse, temperature, breathing, etc.) or the whole body area sensor network. The actuators stand for the devices, used for giving feedback to the user, i.e. it can be a mobile phone, PDA, computer or some other special purpose equipment, used by a patient or medical staff. It should be noted that both, sensors and actuators, can reside on the same physical device, e.g. a wearable band or watch performs both actions –

sensing and actuating, i.e. detecting the pulse as well informing the user upon some deviation from basic parameters. Every physical sensor and actuator is associated with sensor/actuator agents in the virtual environment. Real-time data from physical sensors is constantly being acquired by sensor agents and passed to data collection agents – agents, residing on physical environmental devices with higher processing capabilities. Data collection agents act as mediators operating in between the lowest sensor/actuator and upper decision support agents. After receiving real-time physiological data from sensor agents, data collection agents pre-process it and whenever the values exceed the denoted normal condition thresholds, the information is further transferred to actuation or decision support agents for emergent actions or further inference. Decision support agents can reside both on the central processing unit physically deployed in the environment, or in a remote cloud-based setting, allocating the computational and storage capabilities to remote servers. Any decision upon the feedback is communicated to actuator agents and finally to the end user.

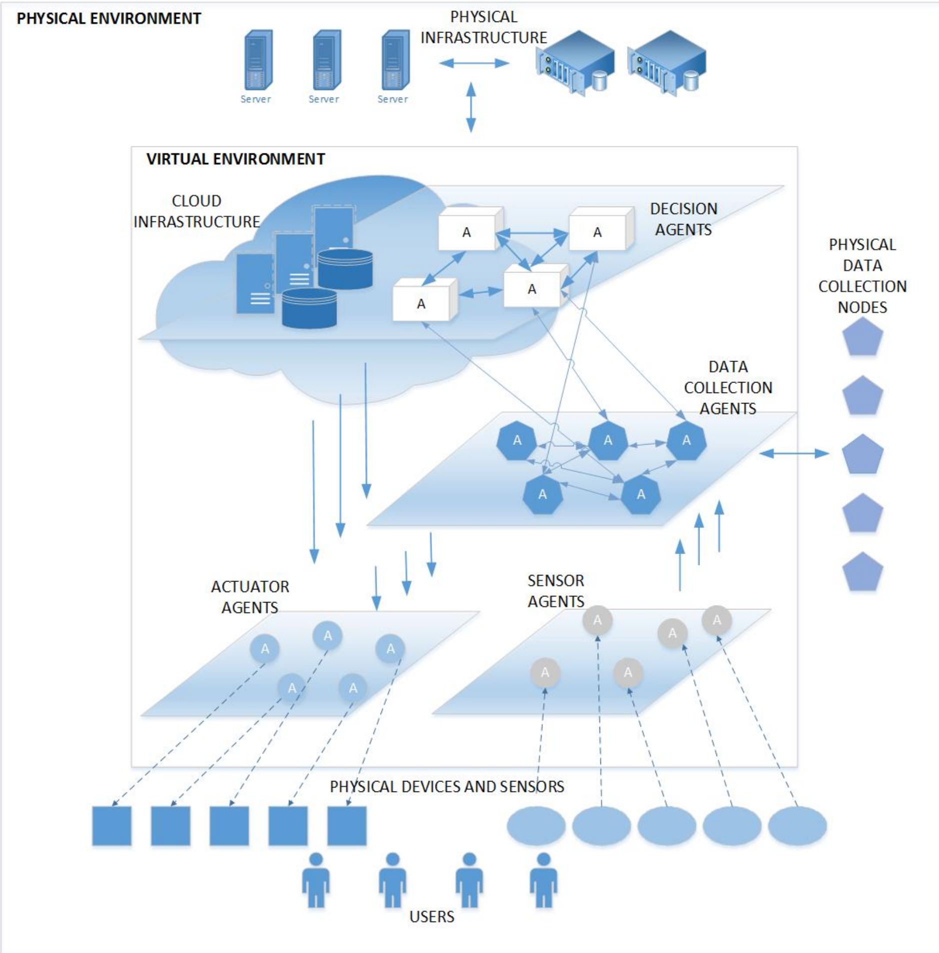

Fig. 1 – Agent-based IoT healthcare system architecture.

2.2. Pulse wave identification method

As it was mentioned before, pulse wave identification method, proposed in [28] was adopted and decomposed according to agent-based approach. In order to correctly identify pulse wave, the algorithm performs several steps. The following functions are analyzed each second, after the data is received:

- Technical and transfer error check.
- Minimum identification;
- Maximum identification;
- Calculating amplitude between minimum and maximum;

- Calculating first point of the waveform to the left of the minimum and first point of the waveform to the left of the maximum;
- Calculating minimum duration of rising edge;
- Checking if rising edge is rising smoothly;
- Similarity with earlier detected pulse wave including: amplitude, minimum and maximum latitudes.

```
Input: data set w(t) collected raw data from pulsewave measuring device.
Array [res(i)] of previously detected pulse waves, i = 1, 2, .., n.
begin
if w(t) < W(max) then
if IsRisingEdgeSmooth(w(t))>1 then
if CompareLenght(w(t))>0,8 then
if CheckSimilarity(w(t), res(n-1))>0,7 then
res(i):=w(t);
i:=i+1;
endif
end
Output: updated array res(i)
```

Fig. 2 – Decision making algorithm.

The algorithm works as shown in Fig. 2. Every data collection agent is associated with the physical pulse wave data registration device, i.e. hardware agent, worn by the patient. Every data collection agent processes the acquired pulse data and performs necessary computations. Any errors detected in any step return the negative result, so further calculations are not conducted, thus saving calculation time and power usage. If the parameters do not exceed the required thresholds, appropriate message is sent to decision agents. As shown in the experiments section, the number of decision agents can be varying. Decision agent then analyzes the results, acquired from all data collection agents and takes decision, whether the pulse wave is detected or not.

3. EXPERIMENTS AND RESULTS

3.1. Experimental setup

The proposed agent-based technique and algorithm were adapted in real world scenario. The conducted experiment allowed testing the proposed theoretical approach in real time IoT environment. The following hardware equipment was required for the experiment:

- Raspberry pi zero – inexpensive low power device with Bluetooth and wireless capabilities – as mobile data collection agents;
- Cms-50f pulse oximeter commercially available device for sensing real time human health parameters – as data reading agent;
- Odroid C2 – small factor quad core full-fledged single-board computer – as stationary decision agent;
- Asus wireless router for transmitting data between agents.

Hardware experimental setup is presented in Fig. 3. As denoted in the picture, devices communicated wirelessly via wi-fi and Bluetooth, transmitting data to data collection agents, where, depending on the different experiment stages, partial or full wave analysis was conducted. The preprocessed data was sent to decision agent, where the decision about the pulse wave was made. The decision data was stored in the database for later access from intranet or internet services.

The software required for the experiment is enumerated below:

- Debian Linux.
- Mysql database.
- Node.js framework with following libraries:

  - Evejs – library enabling agents in node.js.
  - Noble – Bluetooth communication support.
  - Mysql – communication with Mysql server.
- Timeseries – reporting and testing purposes.

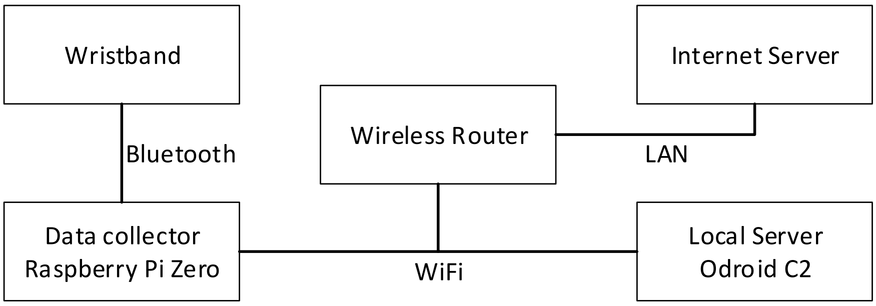

Fig. 3 – Pulse wave detection system hardware setup.

3.2. Results

Real-time experiments were conducted with data from one patient at a time. Preferable agent decision response time would be less than 550 ms, because the processed data still has to be communicated further to actuator agents and sent to the cloud for deeper analysis and prediction. Seeking the optimal processing time, the experiment was performed with one, two, three and four data collection agents and one decision agent respectively. The objective of the experiment was to measure the response time, i.e. to evaluate, whether the agents can return results fast enough for the decision agent to make decision, assuring real time system behavior.

The results of the experiments' are shown in Fig. 4. At first, the identification of pulse wave was performed with one data collection agent and one decision agent, returning the average processing time of 942 ms. During the next experiment, the processing was decomposed for two data collection agents – which gave the average result of 785 ms and in the case of three agents – returning the average result of 643 ms. In all denoted cases the results are insufficient for real-time further processing. Finally, the use of four data collection and one decision agent met the given real-time requirements with average data processing result of 524 ms.

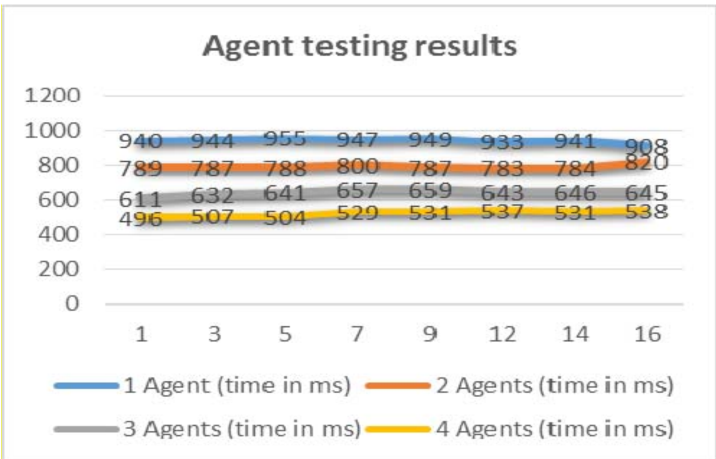

Fig. 4 – Agent testing results.

Total measuring time was 4.5 hours. During that time the algorithm detected 16504 pulse waves (Fig. 5) and identified the corresponding numbers of different noise artifacts: technical errors – 478, length errors – 723, wave dissimilarities – 1278, unstable rising edge artifacts – 1387.

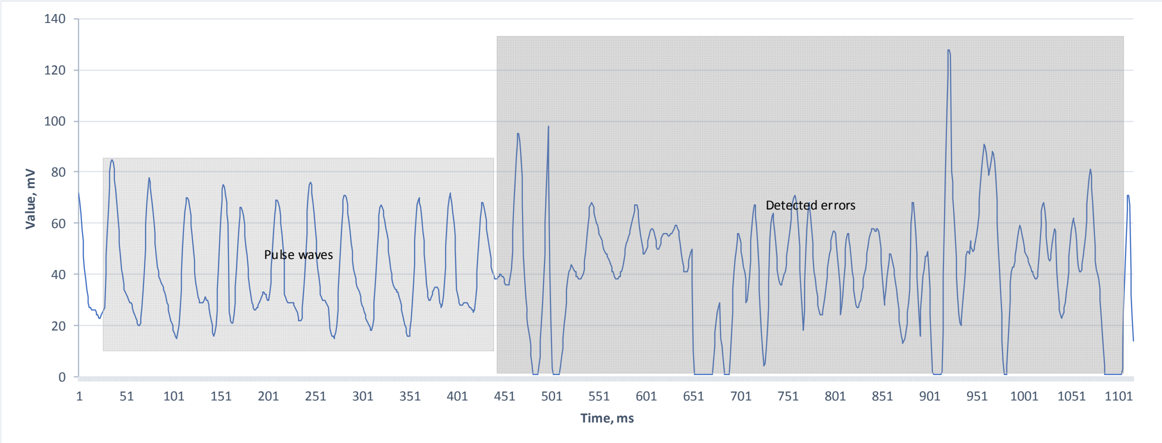

Fig. 5 – Detected pulse waves and errors.

4. CONCLUSIONS AND FUTURE WORK

The experiments showed that the minimal required number of data collection agents in the given specific task was four and it allowed ensuring real time data processing. Though the number of agents would vary depending on every specific case of the application scenario, the denoted experiments confirmed that decomposition of pulse wave identification process to distributed agents lead to significant processing time reduction and validated the feasibility of agent systems for real time IoT healthcare applications.

The present study has investigated the processing time aspect of IoT healthcare systems, consequently further experimental studies are required for evaluating the resource consumption problem. Though present findings conclude that decreased processing time leads to fewer battery resource consumption, further research is needed to evaluate that reduction in terms of concrete numbers. Fewer resource consumption for each agent is achieved due to additional hardware components, thus it is important to evaluate the upside of the prolonged operating time of the IoT system versus the downside of additional hardware costs.

REFERENCES

1. M. HAGHI, K. THUROW, R. STOLL, *Wearable devices in medical internet of things: Scientific research and commercially available devices*, Healthc. Inform. Res., **23**, pp. 4–15. 2017.
2. S. BAKER, X. WEI, I. ATKINSON, *Internet of Things for smart healthcare: Technologies challenges and opportunities*, IEEE Access, **5**, pp. 26521–26544, 2017.
3. M.P. SINGH, A.K. CHOPRA, *The Internet of Things and multiagent systems: Decentralized intelligence in distributed computing*, Proceedings of the IEEE 37th International Conference on Distributed Computing Systems (ICDCS), Atlanta, GA, USA, pp. 5–8, 2017.
4. H. MORA, D. GIL, R.M. TEROL, J. AZORÍN, J. SZYMANSKI, *An IoT-based computational framework for healthcare monitoring in mobile environments*, Sensors, **17**, *10*, p. 2302, 2017.
5. M. HASSAN, W. HU, G. LAN, S. KHALIFA, A. SENEVIRATNE, S. K. DAS, *Kinetic-powered wearable IoT for healthcare: Challenges and opportunities*, IEEE Computer, **51**, *9*, pp. 64–74, 2018.
6. N. SPANOUDAKIS, P. MORAITIS, *Engineering ambient intelligence systems using agent technology*, IEEE Intelligent Systems, **30**, *3*, pp. 60–67, 2015.
7. T. LABEODAN, K. ADUDA, G. BOXEM, W. ZEILER, *On the application of multi-agent systems in buildings for improved building operations performance and smart grid interaction—A survey*, Renewable Sustain. Energy Rev., **50**, pp. 1405–1414, 2015.
8. S. WANG, J. WAN, D. ZHANG, D. LI, C. ZHANG, *Towards the smart factory for industry 4.0: A self-organized multi-agent system assisted with big data based feedback and coordination*, Computer Networks (Elsevier), **101**, pp. 158–168, 2016.
9. J.M. SUCH, N. CRIADO, L. VERCOUTER, M. REHAK, *Intelligent cybersecurity agents*, IEEE Intelligent Systems, **31**, *5*, pp. 3–7, 2016.
10. D. CALVARESI, D. CESARINI, P. SERNANI, M. MARINONI, A. DRAGONI, A. STURM, *Exploring the ambient assisted living domain: a systematic review*, Journal of Ambient Intelligence and Humanized Computing, **8**, *2*, pp. 239–257, 2017.
11. D. ISERN, A. MORENO, *A systematic literature review of agents applied in healthcare*, J. Med. Syst., **40**, *2*, p. 43, 2016.
12. S. IQBAL, W. ALTAF, M. ASLAM, W. MAHMOOD, M.U.G. KHAN, *Application of intelligent agents in health-care: review*, Artif. Intell. Rev., **46**, *1*, pp. 83–112, 2016.

13. E. VARGIU, F. ZAMBONELLI, *Agent abstractions for engineering IoT systems: A case study in smart healthcare,* IEEE 14th International Conference on Networking, Sensing and Control (ICNSC), 2017, pp. 667–672.
14. F. BERGENTI, A. POGGI, M. TOMAIUOLO, *Multi-agent systems for e-health and telemedicine* (chapter) in: *Encyclopedia of e-Health and Telemedicine* (IGI Global), 2016, pp. 688–699.
15. R. COUCEIRO, P. CARVALHO, R. P. PAIVA, J. HENRIQUES, J. MUEHLSTEFF, *Detection of motion artifacts in photoplethysmographic signals based on time and period domain analysis*, Proc. Conf. IEEE Eng. Med. Biol. Soc., pp. 2603–2606, 2012.
16. J. HARJU, A. TARNICERIU, J. PARAK, A. VEHKAOJA, A. YLI-HANKALA, AND I. KORHONEN, *Monitoring of heart rate and inter-beat intervals with wrist plethysmography in patients with atrial fibrillation*, Physiological Measurement, **39**, *6*, p. 065007, 2018.
17. T. TAMURA, Y. MAEDA, M. SEKINE, M. YOSHIDA, *Wearable photoplethysmographic sensors – Past and present*, Electronics, **3**, *2*, pp. 282–302, 2014.
18. M. GHAMARI, *A review on wearable photoplethysmography sensors and their potential future applications in health care*, Int. J. Biosens. Bioelectron., **4**, *4*, pp. 195–202, 2018.
19. M.T. ISLAM, I. ZABIR, S.T. AHMED, M.T. YASAR, C. SHAHNAZ, S.A. FATTAH, *A time-frequency domain approach of heart rate estimation from photoplethysmographic (PPG) signal*, Biomed. Signal Process. Control, **36**, pp. 146–154, 2017.
20. R.R.F. DE LA VARA PRIETO, D.D. RODRÍGUEZ, M.B.C. SANZ, A.S. MENGANA, H.F.P. QUINTERO, *Algorithm for systolic peak detection of pulse wave*, Proc. 38th Conf. Latinoamericana Inform. (CLEI), pp. 1–4, 2012.
21. M.S. ROY, R. GUPTA, J.K. CHANDRA, K.D. SHARMA, A. TALUKDAR, *Improving photoplethysmographic measurements under motion artifacts using artificial neural network for personal healthcare*, IEEE transaction on instrumentation and measurement, **67**, *12*, pp. pp. 2820–2829, 2018.
22. Y. ZHANG, M. HAGHDAN, K.S. XU, *Unsupervised motion artifact detection in wrist-measured electrodermal activity data*, Proceedings of the 2017 ACM International Symposium on Wearable Computers, 2017, pp. 54–57.
23. C. FISCHER, M. GLOS, T. PENZEL, I. FIETZE, *Extended algorithm for real-time pulse waveform segmentation and artifact detection in photoplethysmograms,* Somnologie, **21**, *2*, pp.110–120, 2017.
24. C. FISCHER, B. DOMER, T. WIBMER, T. PENZEL, *An algorithm for real-time pulse waveform segmentation and artifact detection in photoplethysmograms*, IEEE Journal of Biomedical and Health Informatics, **21**, *2*, pp. 372–381, 2016.
25. G. BIAGETTI, P. CRIPPA, L. FALASCHETTI, S. ORCIONI, C. TURCHETTI, *Motion artifact reduction in photoplethysmography using Bayesian classification for physical exercise identification*, Proceedings of the 5th International Conference on Pattern Recognition Applications and Methods (ICPRAM), Rome, Italy, pp. 467–74, 2016.
26. K. M. WARREN, J.R. HARVEY, K.H. CHON, Y. MENDELSON, *Improving pulse rate measurements during random motion using a wearable multichannel reflectance photoplethysmograph*, Sensors, **16**, *3*, p. 342, 2016.
27. S.-W LIOU., D. KURNIADI, B.-R. ZHENG, W.-Q. XIE, C.-J. TIEN, G.-J. JONG, *Classification of biomedical signal on IoT platform using support vector machine*, IEEE International Conference on Applied System Invention (ICASI*)*, 2018, pp. 50–53.
28. B. NENOVA, I. ILIEV, *An automated algorithm for fast pulse wave detection*, Int. J. BIOautomation, **14**, *3*, pp. 203–216, 2010.

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