A Context-Aware IoT-Based Smart Wearable Health Monitoring System

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Abstract*—Development in wearable health monitoring technology has been dramatically improved due to the increasing use of wireless technologies and the miniaturization of electronic sensors. It is the potential to change the future of healthcare services through the use of active health monitoring devices on the Internet of Things (IoT) to track patients and athletes through their regular daily routines. Medical applications such as remote monitoring, biofeedback and telemedicine build a completely new framework for controlling health quality and costs. This work aims to develop a low-cost, high-quality multi-purpose wearable smart device for tracking the health care of patients with heart disease and fitness athletes. In this paper, we discuss our proposed system through three phases. In the first phase, we use the Raspberry-Pi as an open-source microcontroller with a HealthyPi hat serving as a conduit between the Raspberry-Pi and the HealthyPi-connected biomedical sensors with different parameters such as temperature, ECG, pulse, oximetry, … etc. We started our experiment with 15 different test subjects with various gender, ages and levels of fitness. We positioned the proposed wearable device and gathered data on readings for each test subject when sitting, walking and running. The second phase includes linking our device to an open-source IoT dashboard to display the data via an interactive IoT dashboard to be accessed remotely by doctors, as well as introducing rules for action that send alerts to patients and doctors in the event of problems. We developed and tested a Fuzzy Logic system in the third phase, which inputs the data collected from the experiments on the accelerometer, gyroscope, heart rate and blood oxygen level, and provides the physical state (resting, walking or running) as output that helps to determine the patient/athlete's health status. The results obtained from the proposed method show efficient remote health status monitoring of test subjects in real-time through the IoT dashboard, and identification of anomalies in their health status, as well as effective detection of physical motion mode using the proposed Fuzzy Logic system design.

Keywords*— *Raspberry-Pi, Internet of Things, Fuzzy, ECG, Telemedicine, Biofeedback, Accelerometer, Gyroscope, Wireless.

I. INTRODUCTION

An ultimate objective of this research is to develop a multi-purpose system that can be used not only to monitor patients with heart disease or the performance of fitness athletes, but also to be used in rural areas and countries with low healthcare capacity and budgets.

In order to reach the design and method of implementing a multi-purpose wireless monitoring system for patients and athletes, the areas of IoT, telemedicine and biomedical sensors have been researched [1-2].

The importance for patients and athletes of a wireless monitoring system is outlined by remotely identifying the essential health parameters and activities of the patient with the help of sensors located on the human body.

This paper proposes an IoT-based multipurpose real-time system that can exchange medical data between patients and physicians in real-time. This proposed system has a wide range of applications, including but not limited to disease management, such as heart disease, where the patient needs to be continuously monitored, or athlete health status and fitness level monitoring.

Now, we highlight some of the many advantages of the system proposed

- Cost-effective: the patient or athlete can be tracked remotely from any place. This minimizes the cost of travel, the hospital bill and the waste of time for multiple visits.
- Quick services: the system allows health care providers and physicians to provide immediate assistance to the patient.
- Real-time management: this allows the patient to receive immediately the necessary treatment, which helps to avoid further complications.
- Improving the quality of life: the proposed method can also help older people, as well as chronically ill people, improve their quality of life with the aid of health experts who will monitor the health status of the patient, and receive notifications of any anomalies.

Further data analysis is carried out by designing a Fuzzy Logic system using the Mamdani method [17] to identify the type of physical movement that takes place, allowing doctors to fully understand all aspects of the health status of the patient.

This is in addition to providing assurance to fitness athletes about their health status and allowing them to strive to improve their fitness levels [3-6].

II. PROPOSED METHOD

Figure 1 shows our proposed system block diagram, which is divided into three phases.

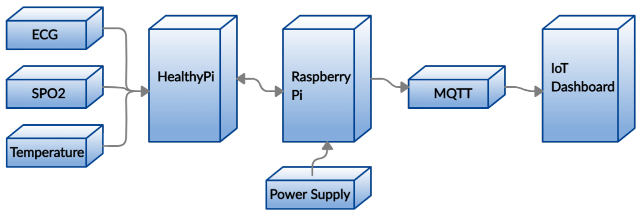

Fig. 1. Multi-purpose IoT ready health monitoring proposed system block diagram.

In the first phase, data collection is initiated by the ECG sensor to collect heart rate, the temperature sensor to collect temperature readings and the SPO2 sensor to collect Oxygen levels and respiratory rate. Data is then transmitted to the HealthyPi device. In its programming code, the controller performs the specified digital signal processing on the raw input data and provides a clear, comprehensible output transmitted to the Raspberry Pi [7-8]. In the second phase, the Raspberry Pi immediately starts transmitting the output data via the MQTT protocol to the selected IoT dashboard.

In the third phase, we use the output data generated to evaluate further and identify the patient/athlete physical and health states. The Fuzzy Logic system that we designed using the Mamdani Fuzzy Inference method uses the output data from the third phase as inputs to the Fuzzy Logic system. The system is supplemented with five inputs; x-direction accelerometer, y-direction accelerometer, y-direction gyroscope, heart rate (HR) and oxygen saturation. For each sensor and each motion type output, the membership functions are determined. Then, using the experiments data readings, we populated the inference engine with our if-then rules to relate the inputs to outputs. The inference engine gets the degree of fulfillment for each input and infers from the fuzzy rules the membership degree of each output. The most likely output is then obtained by defuzzification from the membership degrees of each output.

A. Hardware Components Used in Proposed System

1. Raspberry Pi 3 B+ [9].
2. HealthyPi 3 Hat. [10].

The HealthyPi is a full-featured, open-source monitor for vital signs. It uses Raspberry Pi as its platform for computation and presentation, the HealthyPi add-on HAT transforms the Raspberry Pi into a system for vital sign monitoring.

3. Electrocardiogram (ECG) Sensor ADS1292R [11].
4. Pulse Oximeter Sensor AFE4400 [12].
5. Body Temperature Sensor MAX30205 [13].

B. Software Components Used in the Proposed System

1. IoT Dashboard io.adafruit.com [14].
2. MQTT Protocol [15-16].

The MQTT, Fig. 2, stands for MQ Telemetry Transport. It is a simple and lightweight messaging protocol that uses publish/subscribe, designed for small devices, poor network, limited bandwidth, or high latency.

3. Android Application IoTool.

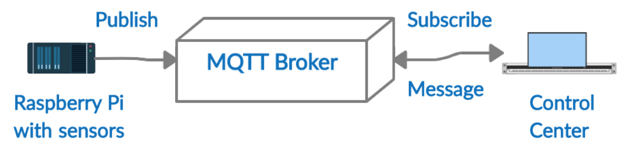

Fig. 2. MQTT protocol block diagram.

III. Fuzzy Logic Algorithm

The Fuzzy logic is a multi-valued logic, with the value of fuzzy variables ranging from 0 to 1. It attempts to model human reasoning and opinion relativity. The membership function is a curve that determines the mapping of each input space to a membership level between 0 and 1. The input parameters of Fuzzy, such as the heart rate numerical value, are represented by a function of a fuzzy membership. Many types of membership functions exist: triangular, trapezoidal, bell-shaped, …, etc. [17].

The Fuzzy inference system attempts to define the fuzzy membership functions to feature vector variables and classes and to deduce fuzzy rules to associate vector inputs to classes [18-19].

Below are the steps of the Fuzzy classification as shown in Fig. 3.

- The sensor set shall be defined as the inputs and the motion mode set shall be defined as the outputs.
- Determination of membership functions: a set of membership functions are defined for each sensor input and motion mode output to associate an input feature value to sets such as "High", "Medium", and "Low."
- Generation of fuzzy rules: IF-THEN fuzzy rules are defined to link the inputs to the outputs through measured statistical data from test experiments.
- Infer output: for each input, the degree of fulfillment (DOF) is obtained, and then the degree of membership of each output is inferred from the fuzzy rules.
- Defuzzification: the most likely output is extracted from the membership degrees of each output [18-20].

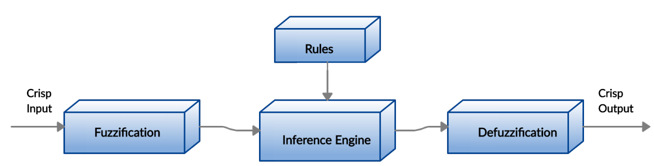

Fig. 3. Fuzzy logic system block diagram [20].

IV. Experimental Work

We began our implementation by using the ECG, temperature and oximeter sensors attached to the HealthyPi hat that is connected to the Raspberry Pi, as shown in Fig. 4, to collect readings of heart rate, temperature, and oxygen levels, respectively. These measurements are obtained from 20 different test subjects with various ages, gender and fitness levels [21-23].

Real-Time presentation of measurements can be viewed on a connected screen if available, as shown in Fig. 5.

The ECG 3-lead electrodes found in Fig. 4 are connected at specific locations on the human body as shown in the color-coded Fig. 6.

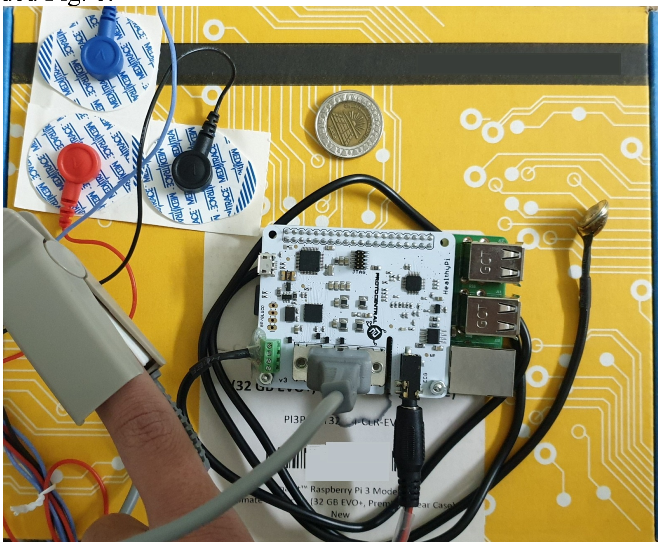

Fig. 4. Real-life system connection.

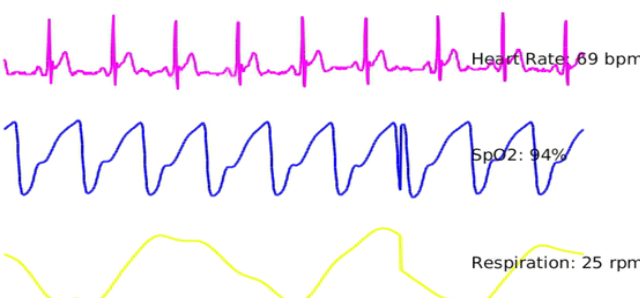

Fig. 5. Real-time data of sensors outputs

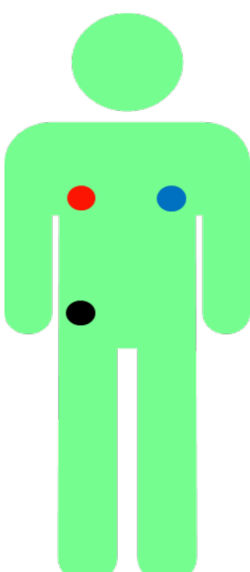

Fig. 6. ECG 3-lead electrodes location.

The readings (results) are collected, leading to constructing Tables I-IV.

TABLE I. RESTING MODE READINGS

Sensor	Ax	Ay	HR	O2	Temperature
Min	-0.01	-0.14	67 BPM	96	36.2°C
Max	0.35	0.58	81 BPM	100	37.0°C

TABLE II. WALKING MODE READINGS

Sensor	Ax	Ay	HR	O2	Temperature
Min	-0.4	-0.45	85 BPM	97	36.4°C
Max	0.66	0.58	102 BPM	100	37.1°C

TABLE III. RUNNING MODE READINGS

Sensor	Ax	Ay	HR	O2	Temperature
Min	-0.6	-0.5	111 BPM	96	36.5°C
Max	0.81	0.95	189 BPM	100	37.3°C

TABLE IV. ALL MOTION MODES READINGS COMBINED

Sensor	Ax	Ay	HR	O2	Temperature
Min	-0.01	-0.14	67 BPM	96	36.2°C
Max	0.81	0.95	189 BPM	100	37.3°C

Using the MQTT protocol and an integrated MQTT client, we were able to transmit this data to our IoT dashboard. It allowed us to track and view a live stream of the health status of the test subject, including the ECG graph, heart rate, body temperature and level of blood oxygen. We have designed our IoT dashboard, shown in Fig. 7 below, to carry out further analysis of the data collected and to send alerts to the patient and doctor if a reading level of a sensor decreases or increases beyond a single point.

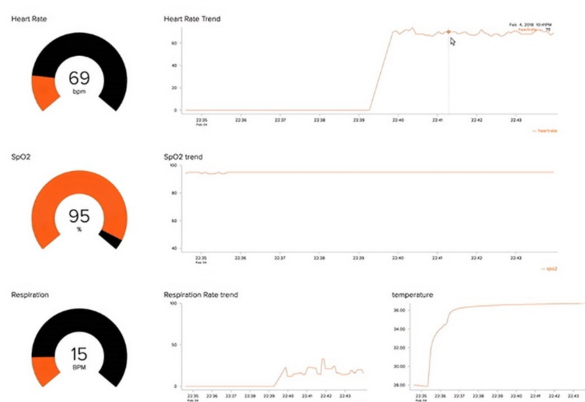

Fig. 7. IoT dashboard real-time data with horizontal axis showing time of day, vertical axis showing sensor reading value

Finally, we created a Fuzzy Logic system using MATLAB, with triangle membership functions that are designed using the Mamdani method. We used five inputs into our system: Accelerometer in the x-direction, Accelerometer in the y-direction, Gyroscope in the y-direction, Heart Rate, and Blood

Oxygen Level. Figures 9-13 show the input membership functions, while Fig. 14 shows the output membership function.

A sample of created rules used by Fuzzy system is shown in Fig. 8 below.

43. If (Ax is L) and (Ay is L) and (Gy is M) and (HR is M) and (O2 is VH) then (Physical-State is Resting) (1)
44. If (Ax is M) and (Ay is M) and (Gy is M) and (HR is M) and (O2 is VH) then (Physical-State is Resting) (1)
45. If (Ax is M) and (Ay is M) and (Gy is L) and (HR is M) and (O2 is VH) then (Physical-State is Resting) (1)
46. If (Ax is M) and (Ay is L) and (Gy is M) and (HR is M) and (O2 is VH) then (Physical-State is Resting) (1)
47. If (Ax is L) and (Ay is M) and (Gy is M) and (HR is M) and (O2 is VH) then (Physical-State is Resting) (1)
48. If (Ax is H) and (Ay is H) and (Gy is H) and (HR is M) and (O2 is VH) then (Physical-State is Walking) (1)
49. If (Ax is M) and (Ay is H) and (Gy is H) and (HR is M) and (O2 is VH) then (Physical-State is Walking) (1)
50. If (Ax is H) and (Ay is M) and (Gy is H) and (HR is M) and (O2 is VH) then (Physical-State is Walking) (1)
51. If (Ax is H) and (Ay is H) and (Gy is M) and (HR is M) and (O2 is VH) then (Physical-State is Walking) (1)
52. If (Ax is H) and (Ay is H) and (Gy is H) and (HR is H) and (O2 is VH) then (Physical-State is Walking) (1)
53. If (Ax is H) and (Ay is H) and (Gy is M) and (HR is H) and (O2 is VH) then (Physical-State is Walking) (1)
54. If (Ax is H) and (Ay is M) and (Gy is H) and (HR is H) and (O2 is VH) then (Physical-State is Walking) (1)
55. If (Ax is H) and (Ay is H) and (Gy is H) and (HR is H) and (O2 is VH) then (Physical-State is Running) (1)
56. If (Ax is VH) and (Ay is H) and (Gy is H) and (HR is H) and (O2 is VH) then (Physical-State is Running) (1)
57. If (Ax is H) and (Ay is VH) and (Gy is H) and (HR is H) and (O2 is VH) then (Physical-State is Running) (1)
58. If (Ax is H) and (Ay is H) and (Gy is VH) and (HR is H) and (O2 is VH) then (Physical-State is Running) (1)
59. If (Ax is VH) and (Ay is VH) and (Gy is VH) and (HR is H) and (O2 is VH) then (Physical-State is Running) (1)
60. If (Ax is H) and (Ay is H) and (Gy is H) and (HR is VH) and (O2 is VH) then (Physical-State is Running) (1)
61. If (Ax is H) and (Ay is H) and (Gy is VH) and (HR is VH) and (O2 is VH) then (Physical-State is Running) (1)
62. If (Ax is H) and (Ay is VH) and (Gy is H) and (HR is VH) and (O2 is VH) then (Physical-State is Running) (1)
63. If (Ax is VH) and (Ay is H) and (Gy is H) and (HR is VH) and (O2 is VH) then (Physical-State is Running) (1)

Fig. 8. Sample of created rules used by Fuzzy system.

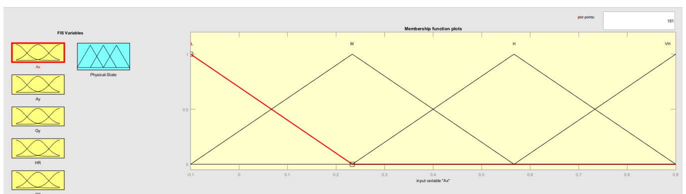

Fig. 9. Membership function for accelerometer in the x-direction.

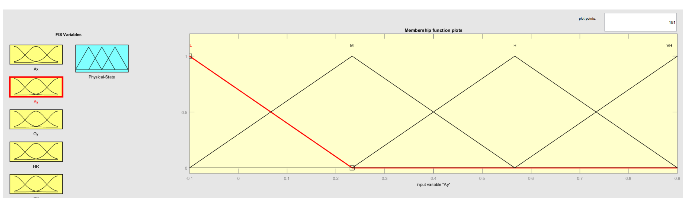

Fig. 10. Membership function for accelerometer in the y-direction.

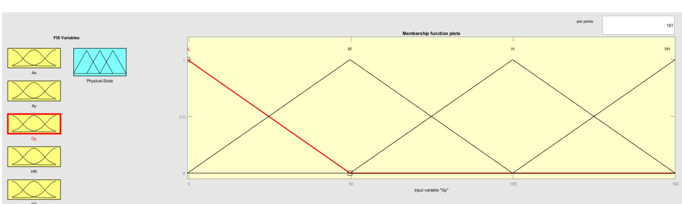

Fig. 11. Membership function for gyroscope in the y-direction.

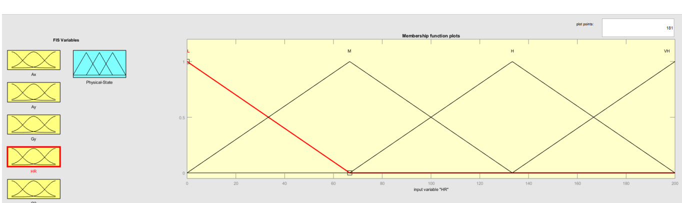

Fig. 12. Membership function for heart rate.

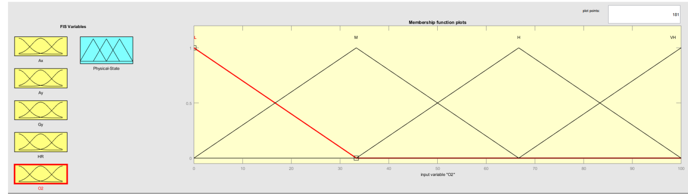

Fig. 13. Membership function for blood oxygen level.

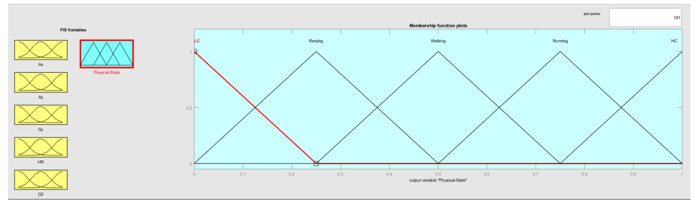

Fig. 14. Membership function for motion mode output.

V. Results and Discussion

Successful implementation of our system allowed us to track the test subjects in real-time, detect any changes in their health status, and carry out further analysis of their collected readings with our MATLAB built Fuzzy Logic system and detect the type of physical activity that occurs. Figures 15-20 show the output detection of different motion modes.

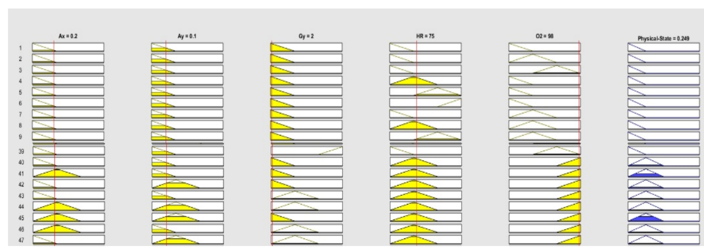

Fig. 15. Output result inferred from rules showing resting mode.

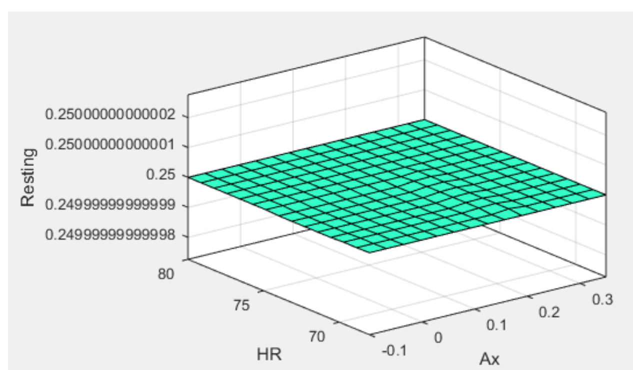

Fig. 16. Predicted output surface between Ax, HR: Rest State.

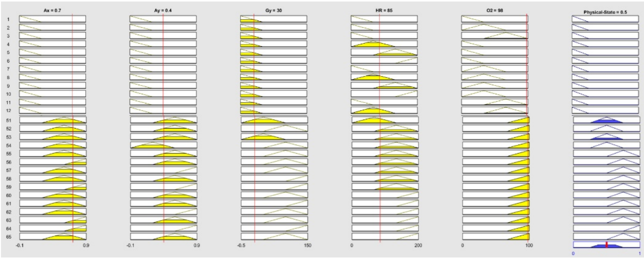

Fig. 17. Output result inferred from rules showing: Walking Mode.

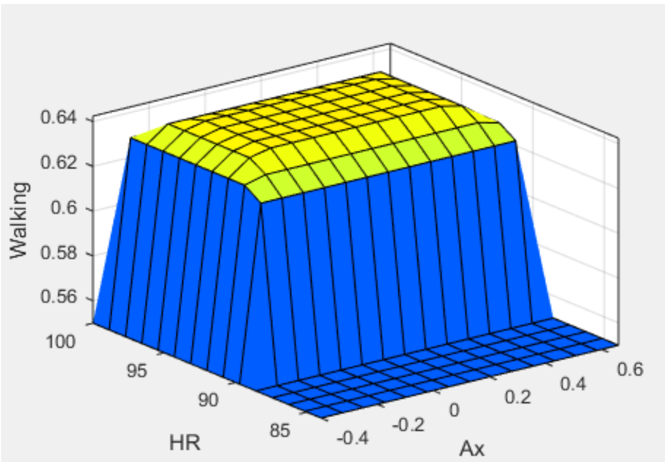

Fig. 18. Predicted output surface between Ax, HR: Walking State.

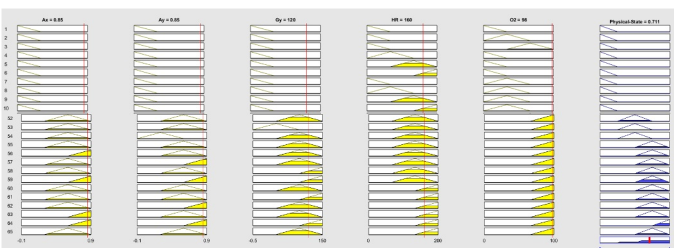

Fig. 19. Output result inferred from rules showing: Running Mode.

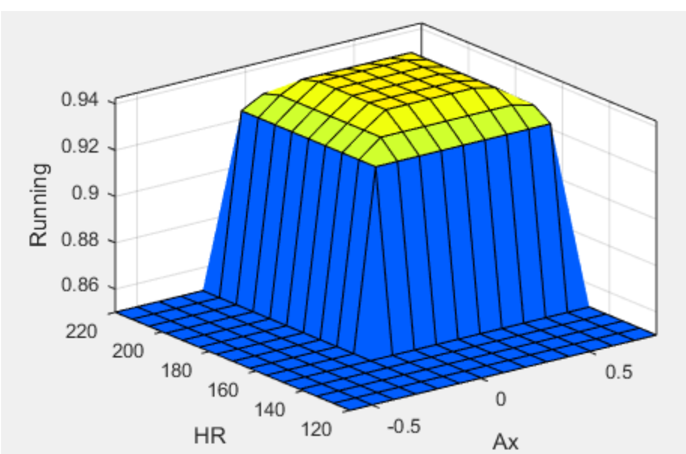

Fig. 20. Predicted output surface between Ax, HR: Running State.

We are also able to provide instant alerts to test subjects and their physicians once the IoT dashboard io.adafruit.com noticed any issues or anomalies in their health status readings. It has been found that body temperature within normal ranges does not vary in physical motion type detection, as the difference in body temperature is minute and is considered negligible in our experiment.

Table V shows the number of effective motion type detection and ineffective detection and the percentage of error after conducting 60 test cases.

TABLE V. DETECTION RESULTS AND ERROR PERCENTAGE

Detection	Resting	Walking	Running
Successful	19	18	18
Unsuccessful	1	2	2
Accuracy	91.6 %		

VI. CONCLUSION

In the areas of healthcare and fitness sports, the importance of having a multi-purpose IoT ready health monitoring system is declared, as well as highlighting the many benefits of such a system in providing patients, athletes, healthcare centers and doctors with a balance between cost, quality and manageability. Using three smart wearable sensors and a smartphone, we were able to capture the health status readings accurately and achieve active tracking of the patient vital signs and effectively transmitting the readings to the IoT dashboard in real-time to be examined by physicians. With high accuracy, the proposed Fuzzy Logic system can detect the correct physical mode of motion.

Using the 60 test cases from our experiments, the proposed Fuzzy Logic system was able to successfully detect the resting motion mode 19 times out of 20, the walking motion mode 18 times out of 20, and the running motion mode 18 times out of 20. Giving the system accuracy of 91.6 % in successful motion mode detection.

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