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A two stages fuzzy logic approach for Internet of Things (IoT) wearable devices

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***Abstract*—In the last few years the process of monitoring people health status has grown in interest in the researcher community and led to the develop of new devices able to detect and analyse information gathered from many kind of sensors. These devices are commonly designed to monitor or diagnose disease in the medical field. Moreover, a remarkable interest is growing in the field of sports.In amateur activities such as jogging, running, climbing a set of smart devices are used to improve and monitor performances. Another field of interest is represented by those people that wants to monitor their health status by using low cost devices. In this work we propose a two stage fuzzy logic approach in which the device tries to learn and fit customer habits in order to discover outlier warning signals. The two stages approach proposed consists of monitoring the normal activities of the user in order to build a reference of its condition; Then a real-time monitoring and analysis of gathered data from body sensors is accomplished. User status is carried out using a Fuzzy Logic based network. First stage will give us the current activity of the user while second stage will provide information about health status in terms of heart rate.**

***Index Terms*—IoT,Wearable,Fitness,E-Health, Health Care.**

I. INTRODUCTION

During last decade, the attention on keeping a good health status through the use of monitoring devices have been grown in interest. These interests regard not only medicine goals but also monitoring performances during sport challenges. Moreover, a lot of money is spent on expensive devices able to gather data about sport performances with the main goal of keeping a good health and improving life quality [1]. In this work, we focus our attention on the realization of a low cost wearable device to collect, analyse and classify data in order to monitor user health status. The device is connected with a cloud system to make a further investigation on collected data as well as analyse them to better fit device parameters to the specific user. In this way there is a continuous parameters customization that adapts the device to the user. The proposed device is composed of a three axis accelerometer, an heart rate sensor and a micro-controller based on the Arduino technology. Moreover,a low-power wireless access device is used to give the possibility to send data towards the cloud system. Received data are analysed in real-time on-board, classified, clustered, and then sent to the cloud. In literature there are interesting works about wearable devices and health monitoring. In [2] the authors give an analytical formulation of the Human Activity Recognition (HAR) problem and its relaxed version; they point out also the design issues of a generic health monitoring architecture. In order to achieve a better solution for the HAR it is important to evaluate the optimal placement of the sensors along the body. Regarding this issue several studies have been made in the last years as shown in [3], [4]. A description of the most used activity recognition method is also presented.The use of information technology and engineering models applied to healthcare environment are shown in [5] with a brief introduction of computational models. In [6] the authors proposed a physiological measurement platform to monitor values like Electrocardiogram (ECG), blood pressure and oxygen saturation. The data exchange is ensured by Zigbee and Bluetooth networks.The authors of [7] provide a comprehensive survey to examine the development and the status of the art of various aspects in sensor-based activity recognition.They also explain and discuss the major differences between vision-based and sensor-based activity recognition. In [8] a novel method to compress the key features vector is proposed in order to reduce the dimension of the problem and mantain the most discriminative information. The results show that their approach boost performances in real-time applications and large-scale dataset processing. In our work we used a sensor based approach to keep the device cost low without any significant loss of accuracy as shown in [11] work. The data are not pre-processed for the real-time analysis but are aggregated before the transmission to the cloud storage. This work is organized as follow:

- In Section I a brief introduction and the status of the art are presented; in particular, solutions designed for the HAR and in the fields of fitness and medicine have been pointed out;
- In Section II the device architecture and some common related issues are presented by pointing out electronics and sensors that are used to build the wearable device;
- Section III presents the analysis of data for the HAR to classify user activities taking into account acquired data from sensors. Here a fuzzy logic analysis is performed for activity recognition;
- Section IV illustrates how HAR is performed in this work; here the fuzzy logic schema has been introduced to recognize the user activity starting from data coming from sensors layer;
- Section V presents how smart device are used to carry out Activities and user status in terms of Heart Beat Rate (HBR);

- Conclusions are presented at last here some comments and future activities will be presented.

II. Smart Device and common issues

In this work our goal is to classify a person behaviour in terms of activities. The classifier has to identify in the most accurate way the activity of the user wearing the device. In this way is possible to map the current heart rate value with reference values previously acquired. In order to achieve these goals we introduce a set of sensors and a micro-controller in the device able to create a Body Area Network (BAN). Through this network the data exchange to and from the wearable devices is performed. These data are used as an input set for the Classifier Module (CM).

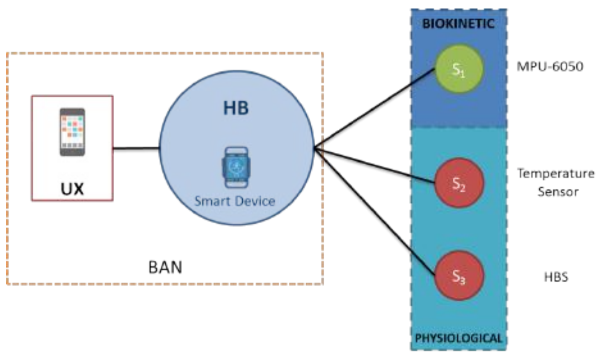

Fig. 1. BAN example where several sensors are connected between them and to a base station that is commonly represented by a smartphone

A. Wearable Device

One of the most important function is the possibility to run several tasks in background avoiding users to interact directly with other software or hardware. Often, the Human Computer Interface (HCI) is considered as a resultant of two separates components, human and computer, but the main goal in this field is to have a joined entity where the human and the machine are strictly connected. The main reason is that we are looking for technologies that help us to make multiple actions in a shorter time. In the medicine fields there are several kind of devices able to work as actuators, such as automatic insulin dispenser, that can be remotely activated under medical control. Most common applications are related to the use of classic sensor designed for the vital parameters monitoring, which are distributed all over the body and are able to communicate with a centralized device such as smartphone or control unit.

B. Sensors

A Body Sensor Network (BSN) is composed by sensors and actuators. Some are less complex like heart-beat monitor sensors others instead could be more sophisticated like auto-injecting syringes able to administer medicine remotely. Several "sensor nodes" are placed on the user body and it is possible to define a general architecture for all of them. These Sensors can be divided in three main groups:

- Physiological Sensors: they measure personal physiologic values like : heartbeat , blood pressure or the electrical brain activity Electroencephalography (EEG)
- Biokinetic Sensors: they measure movements making the architecture space-aware
- Environment Sensors : they measure values from the environment like temperature and humidity

C. Heart Beat Rate (HBR) Unit in fitness applications

During physical activities the heart beat rate increase to ensure the energies that are necessary to the body to support the strain. HBR monitoring represents a very important parameter in physical activities:

- in aerobic activities like running, cycling , cross country skiing HBR monitor helps distributing in a good way physical energies during the whole activity
- in anaerobic activities like weightlifting and heavy athletics the HBR monitor helps recognizing the right recovery times between the physical exercises.

Measuring HBR during physical activities allow to gather important information about energy consumed and about the exercise quality. It also allow to monitor in real time the health status of the person notifying the user if something is wrong. In conclusion HBR data are really important to both aspects: gather information about the activity and monitor the health status of the user.

III. Human Activity Recognition (HAR)

To perform this activity we need to take under consideration how the human body move into the environment. Several techniques could be used some of them are more complex and invasive than others.The main categories of these systems are herein summarized:

- optoelectronic systems are based on the video analysis of markers positioned on the human body. Markers are placed covering some important points of the body. Once coordinates of the marker are known it is possible to track them in a 3-dimensional space calculating their speeds, accelerations and trajectories [9], [10].
- Electromyography (EMG) system evaluates muscles activities monitoring the Muscle Action Potential (MAP). This method offers good performances and low errors but it is invasive and not easy to wear.

A. IoT device Architecture

The designed device is suitable to work in the IoT environment. Sensors are placed directly on the user body creating a BAN when needed. These devices are able to gather kinematic informations in wide environments. Some researchers [11] compared kinematic data extracted from Portable Inertial Systems with data from Optoelectronic systems. They discovered that reported error from kinematic systems are less than 7% compared to Optoelectronic systems. A critical issue common to all measurement systems is the placement of these sensors [4]. There are several studies about sensors' placement on human body and the conclusions are that, for the main physical activities, only two sensors are necessary. The first placed on the upper body and the second on the lower body. Any other applied sensor does not increase in a concrete way the measurement accuracy.

In this work we consider the architecture shown in fig.2 moreover, specification about sensors are herein reported:

- The MPU-6050 sensor contains a Micro Electro-Mechanical Systems (MEMS) accelerometer and MEMS gyro in a single chip. It is very accurate. Therefor it captures the x, y, and z channel at the same time. Sensor uses the $I^2C - bus$ to interface with Arduino [12];
- Heart Beat Sensor (HBS) is a plug-and-play heart-rate sensor designed for Arduino [13];
- Temperature Sensor - Is an electronic sensor that commutes on I^2C;
- BR-LE 4.0-S3A is a novel module with a bluetooth low energy chipset. It is used to connect smart device with a smartphone.

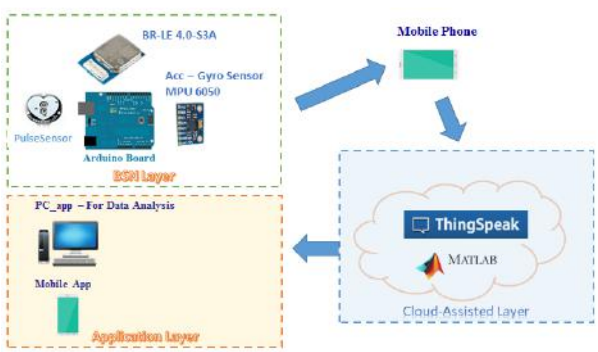

Fig. 2. System Architecture

IV. Physical Activity Recognition

In this work we consider several activities as input for the fuzzy logic. Considered input for the logic block are:

- Resting (R)
- Light Walking (CL)
- Fast Walking (CV)
- Running (C)

As output the fuzzy logic block shall give the following results:

- Resting
- Walking
- Running

A. The Fuzzy Logic

The Fuzzy Logic (FL) challenges and changes the concept of binary logic (only two states): in the real world everything is a matter of measure, not only white or black, but also shades [14]. Unlike the binary logic, to allow a greater relationship with the natural language, the fuzzy sets do not provide ”hard” boundaries but include a landmark change in the considered values. The Membership Degree (MD) of an object referred to a fuzzy set can assume any value in the range [0,1], unlike a traditional set, which is restricted to the values 0 and 1 (false and true): in FL, the MD is to be intended as indicating ”how much” a property is true. Through some input-output relationships it is possible to approximate any function or system to describe or control. One of the most usual inference method is the Mamdani approach [15], divided into four main steps: input fuzzyfication, inference rule evaluation, aggregation and defuzzyfication. The other one is the Sugeno method [16]: the author suggested the use of a single value (singleton) as a membership function. A singleton is a fuzzy set with a Membership Function (MF) that is unitary at a particular point and zero otherwise. The Mamdani method is generally used to describe the knowledge and the experience in an intuitive way, while the Sugeno approach is efficient and it is used in optimization problems or adaptive control.

```
while True do
    gather data from Sensors;
    filter data;
    aggregate data;
    analyze data;
    if is connected to device then
        prepare data for REST service;
        send data to REST service;
        if data sent then
            start from the beginning;
        else
            try to send data again;
        end
    else
        try to peer device;
    end
end
```

Algorithm 1: Smart Device main function

B. Using sensors to recognize activity

In this work we use a fuzzy logic schema to infer info about status of the person that is wearing the device [17]. Main Flow is shown in algorithm algo.1. During the first stage of the main loop device starts to gather data from sensors exploiting the BAN connections. These data are sampled, filtered, aggregated and partially analysed on board. After the device checks connection with the smartphone and if everything is ok it prepares data and send it remotely. In order to avoid bad data set a filtering procedure has been implemented in the smart device. Moreover, It is important to take under consideration where the sensors have to be placed. Several studies have been made in the last few years to evaluate optimal position of the sensors along the body. As shown in [3], [4] it is possible to place a limited number of sensors to gather kinematic data and evaluate the movements. From results shown in [3] it is possible to note that considering single accelerometer sensor, which carries out 3-axes accelerations, it is possible to evaluate several activities with a good percentage of success. We choose to place sensor in the left wrist. For better results it is possible to integrate up to four sensor but this solution might be not comfortable for the users during day activities.

C. Data sampling in IoT on-line service

More complex actions are performed in a non real-time way on the cloud-assisted platform initialized on the Things-peak.com services [18]. Since data transfer is based on a wireless transmission one of the main issue is represented by the power consumption, in fact sending data continuously is not a good idea. Therefore, it is important to find the right trade-off between power consumption and data reliability. In fact, sending data with a low rate may waste the whole data set. Let we explain how data are collected, first of all data coming from body sensors are stored locally and they are processed in the device. This elaboration provides the HAR output by using the FL step.

V. Real case Measurements

In this section the device is presented in a real environment taking into account several measurements made on a pool of people. This pool was heterogeneous and it was composed of young people that presented good health status. Measurements have been compared with reference values carried out from medical instrumentations for HBR; regarding activity recognition we had a direct feedback by knowing user activities. In future works we will ready to compare measurements by directly comparing them with other commercial devices such as wristbands and related applications for HAR. Regarding anomalies on HBR referred to a specific activities we currently worked with a testbed that produced altered values of HBR starting from a real track sample of a healthy person. However, several campaigns about HAR have been performed and good results have been carried out.

A. First Stage : HAR

In the reference block of fig.3 the activity recognition classifier is shown. As it is possible to see this block is built taking into account only acceleration along X and Z axis. In fact, after several observation it has been carried out that the Y-axis is useless for the recognition step.

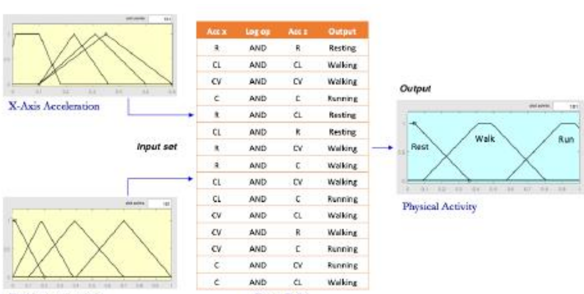

Fig. 3. Fuzzy Physical Activities Recognition Block

it is also possible to note the importance of the acceleration along the 3-axis in the fig.4, fig. 5 and fig. fig.6

Once the Probability Density Functions (PDFs) has been acquired it is possible to model the classifier by defining a set of rules that are shown in fig.3 where the first term is the activity recognized by the sensor related to the X-Axis

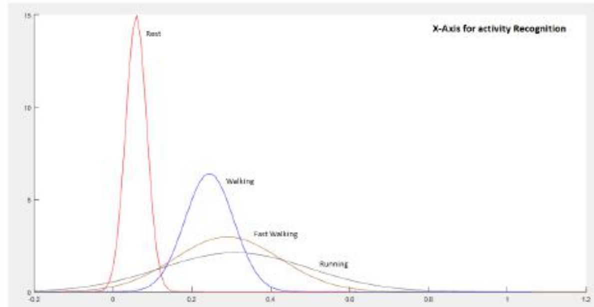

Fig. 4. X-Axis PDF for the STEP-1 of activity Recognition

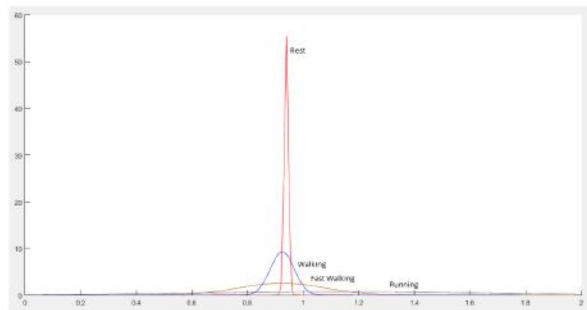

Fig. 5. Y-Axis PDF for the STEP-1 of activity Recognition

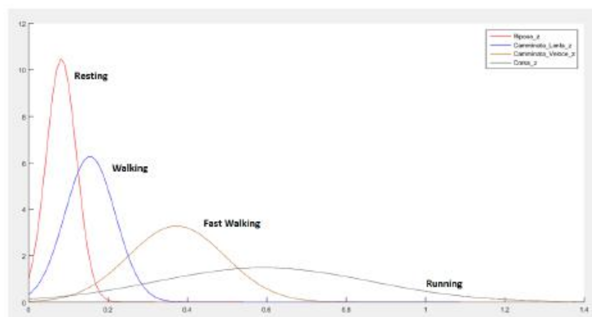

Fig. 6. Z-Axis PDF for the STEP-1 of activity Recognition

acceleration, the second term is the relationship operator to use and the third term is the Z-Axis acceleration. In order to find the output a model has been written in Matlab and it has been ported into the cloud service offered by the ThingSpeak platform. The output is a simplified set of status, which has been already defined (resting, walking and running). This output will be used by the second stage classifier to recognize anomalies of the HBR.

B. Second Stage : Monitoring

The device performs a continuous monitoring of the customer acquiring its HBS, and Bo-kinetic data coming from sensors; these data are used to perform a real-time monitoring. It is important to recall that the device can fit reference data by adjusting parameters during its use.

C. Warning rising

In this section we focused on warning recognition and how to report it to users. First of all the device recognizes individual activity; once the activity is known the right reference data set is considered and used to identify the range of the HBR. This step is performed in a real-time manner using a second step of fuzzy logic that takes into account following status, which are :

- Resting
- Walking
- Running

If something goes wrong and the data acquired from the heart rate sensor are out of range then the device reports warning by sending a "WARNING MESSAGE" to the paired mobile device. This event is also stored in the cloud storage making possible a correct reconstruction of the event. Moreover, in order to better reconstruct the story also the activities' variation are considered as a key-point and therefore they are stored in the cloud storage as well as the warning event.

D. Reference Heart Rate Values

From a deep investigation we discovered some models that could be used to identify the Maximum Heart Rate Frequency (MHRF). In particular, taking into account the model presented in eq.1 it is possible to identify the MHRF, instead by using the eq.2 the feasible range for the HBR can be found. In eq.1 and eq.2 the α term represents the Resting Heart Beat Rate (RHBR) and the β term is the HBR actually measured [19].

$$MHRF = 208 - (0.7 * age) \tag{1}$$

$$MHRF_{Range} = (\beta - \alpha) * \%VO_2max + \alpha \tag{2}$$

For testing scope a deep analysis has been performed with the main goal of finding the right configuration for the system. Once this step has been ended several data set have been created. In fig. 7 the sampled HBRs have been reported, in particular we show the data stored in the cloud for further comparison.

A classifier has been developed taking into consideration equations eq.1 and eq.2 and using the same Matlab tool already shown for the first stage. In particular, we built the PDF model, which has been shown in the fig.8. The difference among HBR here is shown; the HBR shows that each activity has a different impact on heart beating making more different the related PDF. Starting from samples rules are built for the FL classifier.

Making a join among data achieved by the eq.1 and the data obtained by real observation a model for detecting anomalies has been obtained. The output of the fuzzy logic model is shown in fig.9. In fig.9 the classifier is shown starting from the data coming from the HBR sensor and from the knowledge of the activity recognized in stage one. In particular, in the example shown in the left side of the fig.9, for a measurement of 72 bpm and for resting position the output is good with a value of 0.876. Considering the right side of fig.9 a bad condition example is depicted. Here the measured value of 120 bpm for a resting position result in bad condition with a value of 0.124.

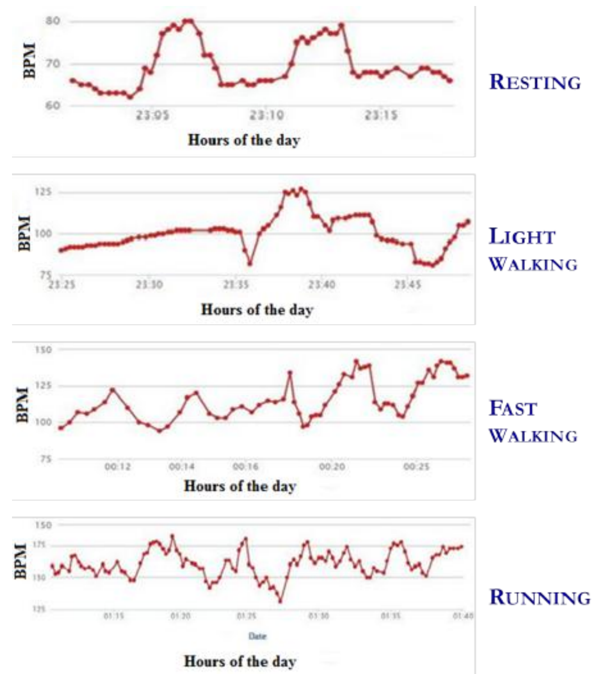

Fig. 7. Sampled data from Heart Beat Rate (HBR) sensor based on the EMG

Fig. 8. PDF model built in MATLAB

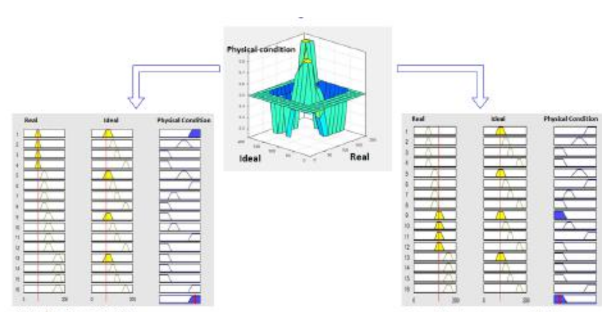

Fig. 9. PDF model built in MATLAB

How this model works: HAR block detects output of first stage and it is used as input for the second stage classifier. HBR is recognized by dedicated sensor and exploiting the BAN this data reaches the smart device. Applying eq.1 the related activity in a normal status can be recognized. Moreover, by using the model that is based on a fuzzy logic block it is possible to raise alarm if data do not match a normal status.

VI. Conclusion

In this work we present a wearable smart device in the IoT domain able to recognize users activities and rises warnings when some outliers are discovered. This mechanism is based on a two stage classifier that use fuzzy logic approach to perform activities recognition and anomalies detection. The core of the device is composed of an Arduino based architecture that is connected with several sensors by creating a BAN. Moreover, to fit the device to the user needs a cloud-assisted architecture has been used for continuously update the settings of the device, which are used by the system to classify activities and for analyse heart rates. The achieved results show that after a bootstrap session where the device learns about user habits and its parameters can recognized the base activities making possible to warn user if something goes wrong about its related heart rate.

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