Unifying Wearable Data: A Novel Architecture Integrating Fitbit Wristbands and Smartphones for Enhanced Data Availability and Linguistic Summaries *

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Abstract. The management of wearable device data faces significant challenges due to the limited availability of suitable Application Programming Interfaces (APIs). In response to this issue, we present a pioneering architecture that seamlessly integrates data from commercially available Fitbit wristbands' sensors and smartphones, resulting in improved data accessibility and advanced linguistic summaries. Our novel approach utilises cutting-edge sensors to efficiently capture and transmit user movement and heart rate data wirelessly to smartphones. A key element of our architecture involves facilitating communication with a central platform via a robust REST API. This enables us to incorporate fuzzy linguistic protoforms, empowering sophisticated data analysis techniques to be employed. Furthermore, we have developed specific applications tailored for both mobile devices and smartwatches, enabling seamless data collection and visualisations. To demonstrate the efficacy and versatility of our proposed architecture, we conducted a comprehensive case study encompassing multiple scenarios. The results of this study affirm the substantial benefits of our approach, showcasing its potential to revolutionise wearable data management and analysis. By providing a scalable and adaptive solution to the current limitations in wearable data management, our work lays the groundwork for further advancements in this field, promising to foster new research and applications in diverse domains.

Keywords: Wearable devices · Data integration · Fitbit wristbands · Linguistic summaries · Mobile data visualisation

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1 Introduction

In the last years, technological advances have been revolutionising the world of wearable devices, providing a wide variety of options for collecting data on users' health and activity [6]. As a result of these innovations, it is becoming increasingly common to find devices that constantly monitor our vital metrics, such as heart rate, sleep quality and physical activity levels [7].

The rise of artificial intelligence (AI) has played a key role in the development of new techniques to extract valuable knowledge from the data gathered by wearable devices [11, 17]. Such technologies enable complex patterns in data to be analysed and understood [14, 15], opening up a world of possibilities in terms of disease detection, early diagnosis and personalised recommendations to improve health and well-being [18, 13].

Another relevant aspect in the area of wearable devices is the use of fuzzy logic, a field of artificial intelligence that allows handling uncertainty and imprecision in the data [1, 2, 4]. This approach is particularly valuable in areas such as healthcare where it has been applied for the early detection of preeclampsia [5], to assess the level of rest [8] or to summarise heart rate streams of patients with ischemic heart disease [16], where the data can vary and are not always absolute.

Regarding wearable devices and existing solutions, some device manufacturers provide APIs to obtain health and activity data, although it is important to keep in mind that many times this data has undergone some kind of processing before being presented to the user. This can involve the transformation of the original values or the application of filtering algorithms, which prevents perform own data processing for other purposes, such as the detection of specific activities or the implementation of custom algorithms. In this sense, wearable devices that provide access to raw data are crucial to enable researchers, developers and professionals in healthcare and other fields to perform in-depth, personalised analysis. The availability of real, unmodified values provides the opportunity to harness the full potential of techniques such as artificial intelligence and fuzzy logic.

In order to address these limitations, the development of a new, advanced and scalable architecture is proposed in this contribution. This architecture will focus on the efficient collection of raw data, allowing users to access all information and providing the opportunity for customised, in-depth analysis. A highlight of this architecture will be its ability to generate linguistic summaries, which will provide a clearer and more accessible comprehension of the data streams.

To evaluate the efficacy and potential of the proposed architecture, a comprehensive case study has been meticulously conducted, comprising three distinct scenarios.

This contribution is structured as follows: Section 2 presents the initial concepts related with linguistic protoforms. Section 3 presents the advanced architecture for wearable device data management. Section 4 presents the proposed linguistic protoforms for evaluating data streams. Section 5 presents a case study to illustrate the capabilities of the proposed architecture. Finally, Section 6 presents the conclusions.

2 Background

This section reviews the fundamentals of linguistic protoforms, which are used in the approach proposed in this contribution, as well as introduce the chosen wearable device for data integration.

2.1 Linguistic protoforms background

In the context of fuzzy logic, linguistic variables play a fundamental role by enabling the representation and description of information in a more flexible way and closer to natural language. These variables are built from a base variable, which takes real numerical values in a given range [20].

To approximate these real values to linguistic terms, fuzzy sets are used, where each linguistic term is bound to a membership function. This membership function establishes the degree of membership of a given value to the corresponding linguistic term. The membership degree is expressed in an interval between 0 and 1, indicating the extent to which the given value conforms to the linguistic term in question [12].

Fuzzy protoforms, on the other hand, originated as a model proposed by Zadeh in the field of fuzzy knowledge [19]. These are based on fuzzy sets whose membership degrees are determined by fuzzy membership functions. These protoforms make it possible to describe and represent processed information using natural language, which facilitates the interpretation and understanding of the results obtained from fuzzy data [9].

2.2 Wearable device

The chosen wearable device to enrich the proposed architecture is the Fitbit Versa 3, although other models may also be considered. The Fitbit Versa 3 is an advanced wearable equipped with a diverse array of sensors, enabling comprehensive data tracking. These sensors include an optical heart rate monitor that continuously measures heart rate, an accelerometer + gyroscope combo for monitoring movement, a barometer for assessing atmospheric pressure changes, a built-in GPS for precise outdoor activity tracking, and an SpO2 sensor for monitoring blood oxygen saturation levels. The choice of this device was based on its popularity, accuracy and ease of use.

3 New proposed architecture

This section presents the proposed architecture for managing data from wearable devices, Figure 1. The different layers that compose the architecture will be described.

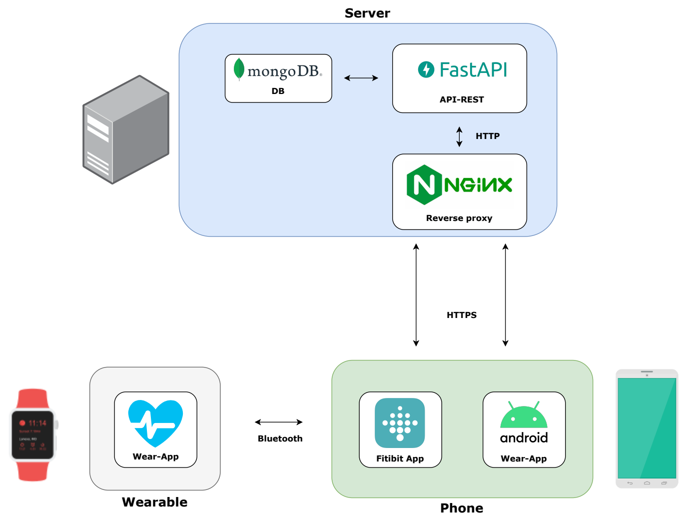


Fig. 1: Architecture of the system.

3.1 Server

This layer in the proposed architecture consists of three main elements: a reverse proxy, a REST API and a database. These elements play key roles in processing, storing and accessing data collected from wearable devices.

Reverse proxy The reverse proxy acts as an intermediary between clients and the server, optimising inbound and outbound requests, enhancing performance, security, and scalability. In this architecture, it serves as a TLS termination proxy, ensuring security by managing TLS protocol termination for communications. This focus on TLS versions 1.2 and 1.3 and strong encryption algorithms enhances security while limiting backward compatibility with legacy clients. The reverse proxy also implements measures against attacks, like denial-of-service (DoS) attacks, to safeguard data and maintain high data availability.

Database The decision to adopt a NoSQL database, specifically MongoDB, in the proposed architecture is driven by the need for flexibility and compatibility with various data-generating devices, not limited solely to Fitbit devices. MongoDB's document-based data model, utilising JSON documents for storage, facilitates efficient data management. This choice enables the system to handle heterogeneous data from diverse devices effectively [3].

API-REST This component performs a fundamental role in the communication between the different clients, allowing data to be exchanged efficiently and securely. The REST API [10] defines a set of endpoints that represent different operations and resources available in the system. This set of resources and operations allows the different applications that make up the architecture to exchange the information needed to operate. The API has been developed using FastAPI [3], a web framework for the development of high performance APIs in Python. Among the advantages of using this framework are the ability to produce interactive documentation through the use of Swagger [4] and the ability to perform automatic validation of data types through Pydantic [5].

3.2 Devices

This layer is made up of the different applications and devices that are responsible for providing and managing the architecture's data.

Wearable Fitbit Versa 3 offers the possibility of developing specific software, which makes it possible to customise the types of data collected as well as their frequency. In this sense, the information retrieved from the device corresponds to heart rate and acceleration, whose data collection frequencies have been set at 1 Hz and 50 Hz, respectively. The information obtained from the device is sent via Bluetooth to a service running within Fitbit's proprietary application on the mobile device. From this service the information is sent to the server via the previously mentioned API.

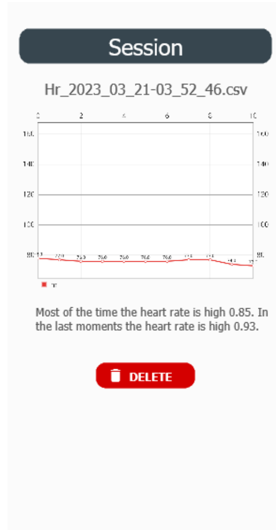
Phone Within the applications that have been developed, there is one that has been designed for mobile devices, Fig 2. The purpose of this application is to ease the management of sessions or data linked to the user's account. This application also allows the visualisation of data streams and protoforms related to these streams, allowing their analysis in an intuitive way. As noted above, given that data cannot be retrieved directly from the Fitbit application, this application connects directly to the API that has been developed to obtain the data linked to the different users. The application performs data persistence, therefore when it synchronises with the server, it will download those sessions that are not available on the device. At the same time, in case of data loss from the server, it will upload those sessions that are not available on the server.

4 Proposed linguistic protoforms

In this section section presents the formal representation of sensor streams and the linguistic protoforms used for describing the data streams of wearable devices.

[3] https://fastapi.tiangolo.com/
[4] https://swagger.io/
[5] https://docs.pydantic.dev/latest/

(a) Saved sessions



(b) Graphic and linguistic summary of the session

Fig. 2: Mobile application developed

4.1 Linguistic expressions for sensor streams

The sensor stream s^j consists of values $s^j = \{m_i^j\}$, where $m_i^j = \{v_i^j, t_i^j\}$ represents the value and timestamp for sensor j at time t_i.

The protoform has the structure: $Q_k\ V_r\ T_j$, where V_r is a crisp term linked to event r, and T_j is a Fuzzy Temporal Window (FTW) aggregating event V_r. FTWs are defined by the temporal distance $\Delta t_i = t^* - t_i$ using membership function $\mu_{T_j(\Delta t_i)}$.

An aggregation function of V_r over T_j computes a unique degree representing the occurrence of event V_r within the temporal window T_j. The subsequent t-norm and t-conorm operators have been established to combine a linguistic term and a temporal window:

$$V_r \cap T_j(\bar{s_i^l}) = V_r(s_i^l) \cap T_j(\Delta t_i) \in [0,1]$$

$$V_r \cup T_j(\bar{s_i^l}) = \bigcup_{\bar{s_i^l} \in S^l} V_r \cap T_j$$

Q_k serves as a fuzzy quantifier k responsible for filtering and transforming the aggregation degree. It applies a transformation $\mu_{Q_k} : [0,1] \to [0,1]$ to the aggregated degree.

4.2 Linguistic protoform based on Heart Rate

As previously mentioned, among the different values that the wearable device collects is heart rate. We propose four fuzzy terms: *low, moderate, high, very high*. The following fuzzy sets are defined using trapezoidal and triangular membership functions for heart rate, expressed in beats per minute (bpm), Figure 3.
$\mu HRL(vhr)$: *TS(0,0,50,60)* $\mu HRM(vhr)t$: *T(50,80,100)* $\mu HRH(vhr)$: *T(80,120,140)* $\mu HRVH(vhr)$: *TS(120,140,200,200)*

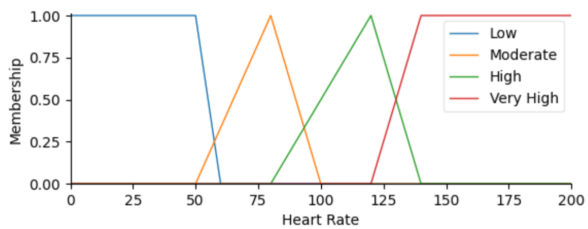


Fig. 3: Membership functions of the fuzzy terms of variable heart rate.

In addition, three fuzzy quantifiers, *part of the time*, *half of the time* and *most of the time*, defined by Gaussian and sigmoid membership functions, Figure 4, are define
$PartOfTheTime(\Delta t)$: *S(50, -0.1)* $HalfOfTheTime(\Delta t)$: *G(50, 10)* $MostOfTheTime(\Delta t)$: *S(50, 0.1)*

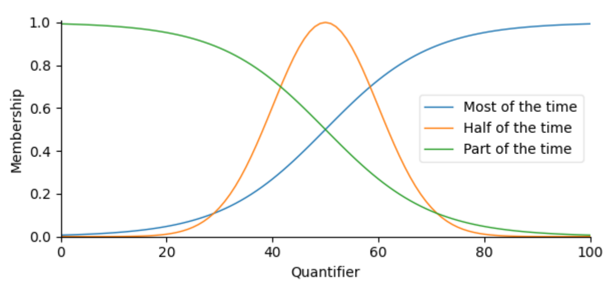


Fig. 4: Membership functions of the fuzzy quantifiers.

Based on the fuzzy sets and fuzzy quantifiers defined above, linguistic protoforms can be constructed as follows:

– $Protoform_1$:*Most of the time the heart rate is moderate*

This type of protoform aims to express concisely in natural language the general behavior of the heart rate during the development of different exercises or sports activities.

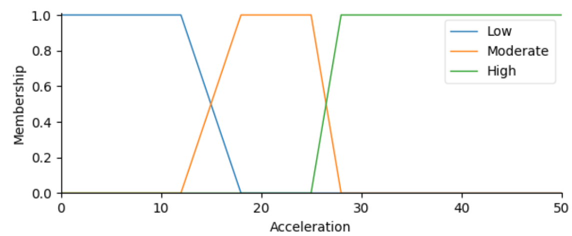


Fig. 5: Membership functions of the fuzzy terms of variable acceleration.

Finally, a fuzzy temporal window, *at the last moments*, is defined by means of a sigmoidal membership function.
$InTheLastMoment(\Delta t)$*: S(10, 0.6)*

This allows the creation of linguistic protoforms such as:

– $Protoform_1$:*In the last moments, the heart rate is very high.*

These protoforms are particularly useful, since during the final stages of certain exercises, the intensity increases, which allows us to make a comparison with the rest of the exercise.

4.3 Linguistic protoform based on Aceleration

Three fuzzy terms, *low, moderate and high*, which are defined by trapezoidal membership functions, are proposed for acceleration analysis. $\mu AL(va)$*: TS(0,0,12,18)* $\mu AM(va)t$*: TS(12,18,15,28)* $\mu AH(va)$*: TS(25,28,50,50)*

Combined with the fuzzy quantifiers defined above, linguistic protoforms of the following type are formed:

– $Protoform_1$:*Part of the time acceleration is high*

5 Case study

In this section a case study composed of different scenarios will be presented, whose objective is to evaluate the proposed architecture. For this purpose, a series of exercises are proposed, where a data collection frequency of 1 sample per second for heart rate and 50 samples per second for acceleration will be set.

5.1 First scenario based on relaxation exercises

The first scenario of the case study involves performing relaxation exercises, which involve alternating between different postures.

Acceleration variations can be noted when changing posture, as shown in Figure 6, while heart rate is maintained at normal levels.

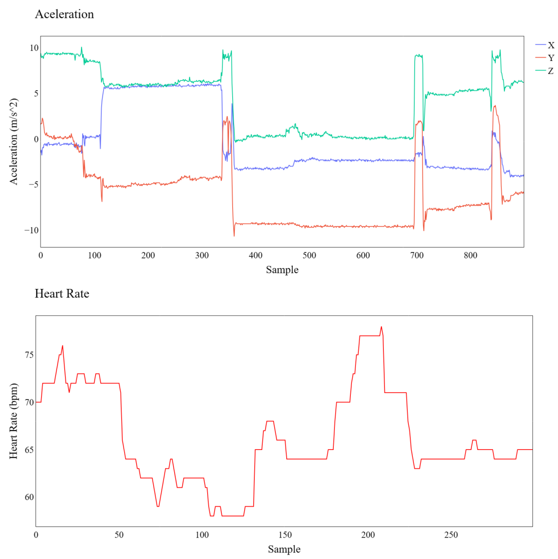


Fig. 6: data streams of the first scenario.

As for the linguistic protoforms, the data obtained for heart rate are as follows: Most of the time the heart rate is normal 0.99. In the last moments the heart rate is normal 0.5. While for the acceleration it has been obtained: Most of the time the acceleration is low 0.99.

5.2 Second scenario based on moderate-intensity exercise

The second scenario of the case study consists of moderate-intensity exercise, specifically focused on bodybuilding.

Figure 7 shows discernible patterns in acceleration, which are related to bodybuilding exercises. In addition, with regard to heart rate, its evolution can be observed as the different exercises are carried out.

In relation to the protoforms, the following results are obtained: Half of the time the heart rate is high 0.73. In the last moments the heart rate is very high 1.0 and Most of the time the acceleration is low 0.99. It is interesting to note that, although the acceleration is higher compared to the previous case, it is still classified as low, suggesting the need to adjust the membership functions. However, as for the heart rate, we find useful information, such as the fact that at the end of the exercise, the heart rate is very high.

5.3 Third scenario based on high intensity exercises

The third scenario of the case study involves the performance of high intensity exercises. In this case, the exercise known as "burpees" has been selected as the specific exercise to be performed.

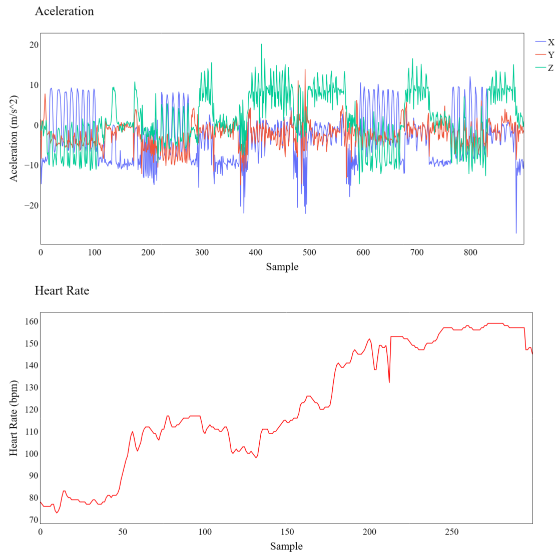


Fig. 7: data streams of the second scenario.

During this scenario, a series of four repetitions of burpees is performed. A burpee is an exercise that involves a combination of movements such as a push-up, a vertical jump and a squat. This exercise is characterized by its high cardiovascular and muscular demand, making it an intense activity.

Based on Figure 8, both high accelerations and high heart rate can be observed.

Regarding the obtained linguistic protoforms, we have the following results: Most of the time the acceleration is high 0.71 and Most of the time the heart rate is very high 0.99. In the last moments the heart rate is very high 1.0.

6 Conclusions

In this contribution, a new advanced architecture for wearable device data collection and processing has been proposed. Compared to other commercial alternatives, this architecture provides raw data, allowing the most appropriate processing to be applied to each user's individual requirements.

Furthermore, an additional approach is provided by the application of linguistic summaries based on the use of fuzzy logic. These linguistic summaries ease the analysis of the collected data by providing an intuitive and understandable representation of the data, thus facilitating interpretation and informed decision making.

In addition, a comprehensive case study has been developed, comprising various scenarios, to evaluate the proposed architecture thoroughly. This case study served as a valuable tool for assessing the effectiveness and practicality of the proposed architecture.

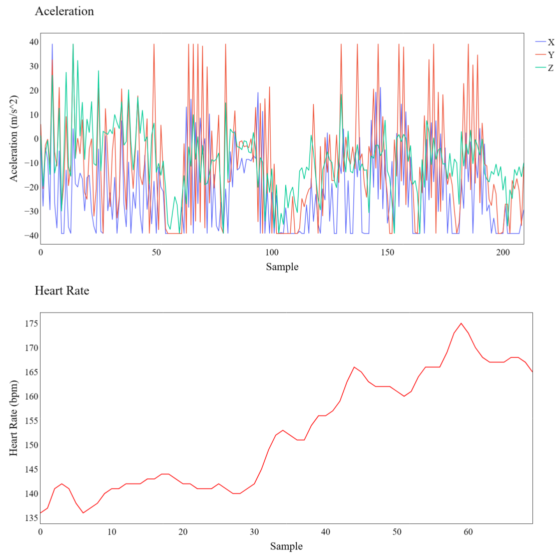


Fig. 8: data streams of the third scenario.

In future work, we intend to further improve this architecture by incorporating more complex and personalised fuzzy protoforms, so that they can describe more accurately and in more detail the data streams.

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