

# The Role of Data Storage in the Design of Wearable Expert Systems

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**Abstract.** Wearable technologies are transforming research in software and knowledge engineering research fields. In particular, expert systems have the opportunity to manage knowledge bases varying according to real-time data collected by position sensors, movement sensors, and so on. This opportunity launches a series of challenges, from the role of network technologies to allow reliable connection between applications and sensors to the definition of functions and methods to assess the quality and reliability of gathered data. In this paper, we reflect about the last point, presenting recent reflections on the wearable environment notion. An architecture for the reliable acquisition of data in the IoT context is proposed, together with first experiments conducted to evaluate its effectiveness in improving the quality of data elaborated by applications.

**Keywords:** Wearable Expert Systems, Internet of Things, Data Storage

## 1 Introduction

Wearable environments [1] have been introduced as conceptual and computational platforms for the development of wearable expert systems (WES) [2], i.e. expert systems capable to interact with wearable devices and sensors to maximize their performance.

This paper presents recent developments and future challenges for this research field, taking care of the possibilities offered by IoT infrastructures. We focus on data storage, given that IoT applications produce massive data from sensors, that require large storage space [3] and opportune mechanisms to optimize their use by applications [4].

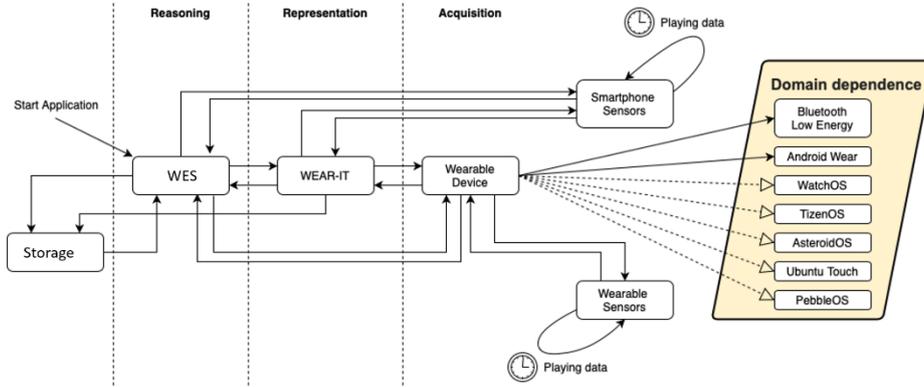
The integration of KAA<sup>1</sup>™ in the wearable environment architecture is a crucial step to develop new services and functionalities supporting wearable expert systems, thanks to its capability to manage data coming from multiple sensors, storing them in both SQL and NoSQL databases, and delivering interfaces to visualization software.

The content of this paper is an attempt to launch new challenges in the wearable environment definition and is organized as follows: Section 2 describes the wearable environment notion from the conceptual point of view, pointing out the data storage role with respect to its components. Section 3 further describes the features of data storage in the wearable environment context, introducing its functionalities and components to deliver them. Section 4 illustrates a case study on analysis of data reliability starting from an existing dataset. Finally, Section 5 briefly highlights lessons learned and challenges for future research.

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<sup>1</sup> <https://www.kaaproject.org/>

## 2 Wearable Environment Model



**Fig. 1.** The Wearable Environment conceptual model

A wearable environment (WE) is a conceptual and computational framework to allow the development of wearable expert systems in the IoT context.

The main rationale between the WE notion is the following:

- Given that expert systems can profitably exploit wearable technologies to gather (possibly real-time) data to run their decision-making process.
- Given that the expert systems development process is divided into knowledge acquisition, knowledge representation and reasoning steps.
- Given that the reasoning step should be able to work on possibly incomplete data sets coming from heterogeneous sources.

Thus:

- The expert system application should be able to accomplish its algorithm without worrying about data format and availability.
- The expert system should interact with an opportune middleware that, considering application desiderata in terms of sensors/wearable device to use, amount and frequency of data to acquire and format to represent acquired data, provides the application with an opportune API to avoid the overlapping among acquisition, representation and use of knowledge/data in the expert system code.

In other words, the wearable environment concept allows the correct and clear separation of expert systems cycle of life, avoiding that knowledge engineering bottleneck [5] problems arise.

Fig. 1 shows the main components of the WE conceptual model:

- **WES:** Wearable expert systems running on the user smartphone are the heart of reasoning level; the execution of a WES is the starting point of the WE cycle of life.

From now on, the wearable environment will be responsible for the correct interaction between the application(s) and the other components involved, i.e. Wear-It and wearable devices/sensors (see below).

- **Wear-It [1]:** namely *Wearable Environment Acquisition and Representation-Infrastructure*, it provides the WES with a complete API for querying sensors on wearable devices and to archive/access data on/from *storage*.
- **Smartphone:** it is both the data collection hub for the Wearable Devices and a data-generating device itself (through its built-in sensors, such as the accelerometer), being also equipped with heterogeneous connectivity capabilities.
- **Wearable Devices:** they connect to the WES (via the Smartphone) through the Wear-It API for the delivery of generated data.
- **Storage:** it is the source of data for WES, managed by Wear-It. Moreover, it provides the user with a set of functions to check the quality of data acquired from sensors, to be sure that the WES will be able to exploit them when necessary. These functions are the subject of the next section.

### 3 Data Storage

The Wear-It development has enabled wearable expert systems to choose the better device to gather data from. Anyway, this is a limit of the framework, since only one device can be paired with the running application. Although this is not a problem from the expert system execution point of view (an expert system is, theoretically, able to work when needed data are incomplete or partially correct), the main drawbacks of this solution are:

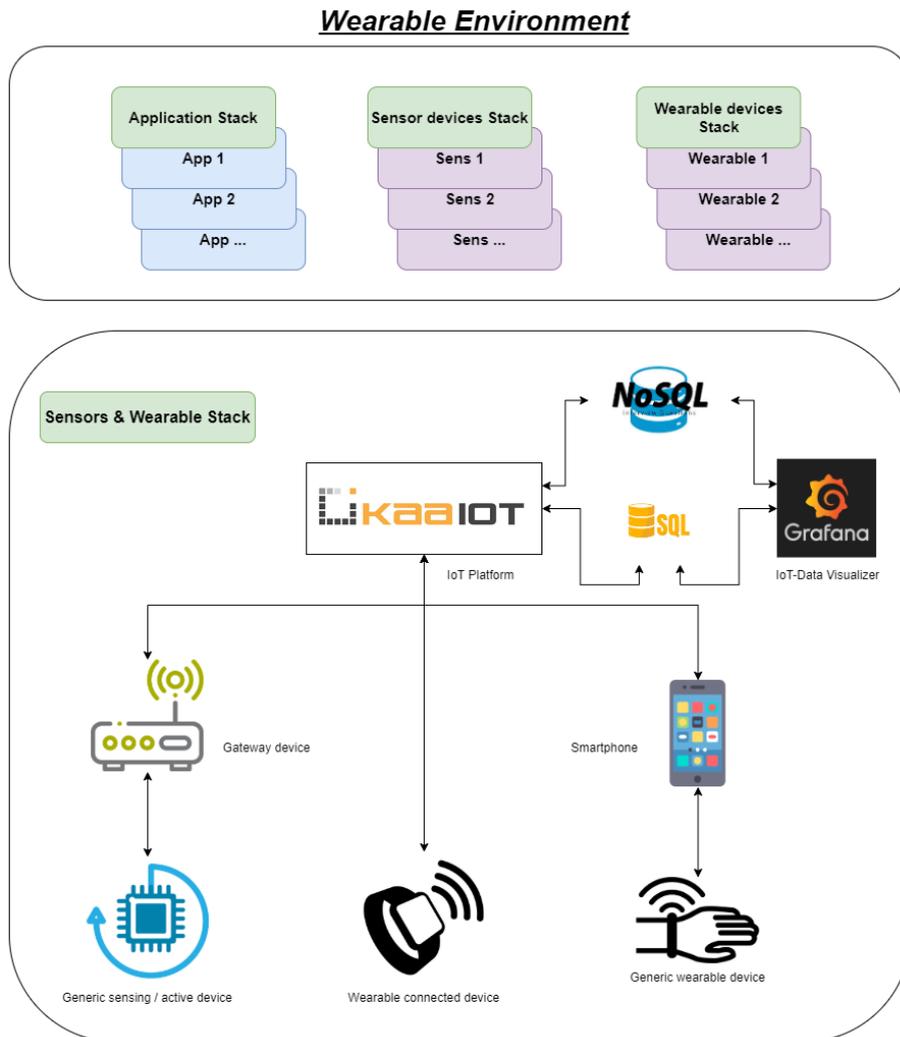
- The impossibility to obtain the best solution from the reasoning strategy.
- The impossibility to verify the reliability and quality of data gathered from sensors.
- The impossibility to select data from multiple sources.

This means that, for example, in case of a wearable expert systems working on environmental data, the decision-making process will answer according to the data detected by a single sensor. What about the possible fault of this sensor? The answer of the system could be wrong or not precise, and the user could be not aware of this mistake. In order to overcome these problems, we have considered to extend the wearable environment to include data management functionalities. As shown in Fig. 1, we envision data *storage* external to the wearable environment levels, but complementary to them.

Data storage is composed of the following parts:

- **Working Station:** it can collect remote data from user's wearable environments and is used to interact with them. It is also equipped with a *Network Module* with advanced *network connectivity* features, being able to autonomously negotiate with multiple fixed, wireless and mobile network providers the creation of *end-to-end (e2e) connections* with the users' Smartphone, relying on the *network slicing* [6][7] concept.

- **IoT Platform:** it runs on the Working Station and supports Wear-It APIs, used by the user's App for the remote management of the wearable environment (e.g. request for collection of specific data from the Wearable Devices, configuration of a Wearable Device, etc.). It also guarantees users' data persistency.<sup>2</sup>



**Fig. 2.** The IoT framework in a WE: KAA™ provides data storage functionalities.

Fig. 2 shows a sketch of the data storage architecture in a wearable environment. The focus here is on the adoption of KAA™ platform to export data management

<sup>2</sup> See <https://grafana.com/>

functionalities. Data acquired from many wearable devices can be managed by it, to allow WES at reasoning level to export data correction, completion (thanks to both SQL and NoSQL databases integration), and visualization (thanks to Grafana integration).

## 4 Case Study

Let us supposed to have an IoT device to measure temperature, *humidity*, *luminosity* and *battery voltage* for a period of 36 days; the dataset [8] simulates this situation and has been historicized in KAA: the resulting table contains 2313682 records. An analysis of anomalies has been conducted on these records, looking for out of bound and null values within them, according to the acceptable values summarized in Table 1, derived from the distribution of values for each variable.

**Table 1.** Acceptable values for data in the case study

Measurement	Minimum Value	Maximum Value
Temperature	-15°C	+50°C
Humidity	0%h	100%h
Luminosity	0 Lux	2500 Lux
Voltage	1.5 Volts	3.5 Volts

The analysis on the records has allowed to identify 407997 anomalies for the temperature variable, 299084 for the humidity variable, 8 for the voltage variable and 0 for the luminosity variable. Then, a first intervention has been the nullification of outliers. This operation is coherent from the expert system point of view, since null values are generally ignored by rules antecedents, while outliers are considered, with possible mistakes in the right-hand sides execution. This simple intervention has allowed to reduce the standard deviation of each variable, with significant benefits from the reliability of source data perspective.

Measurement	Original Std. Deviation	Modified Std. Deviation
Temperature	4.04	2.68
Humidity	6.92	5.73
Luminosity	503.28	503.28
Voltage	0.17	0.12

## 5 Conclusion and Future Works

This paper indicates how data storage can be exploited to improve the overall performance of wearable environments in supporting wearable expert systems. Thanks to the integration of IoT platforms like KAA, data analysis can be improved, with the possibility to design opportune solutions to increase the quality of data acquired by sensors and, consequently, the quality of suggestions proposed by application at reasoning level of a wearable environment.

Future works are devoted to implement such solutions: in particular, the spatial-temporal algorithm presented in [9] will be exploited as a starting point.

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