Merging Smart Wearable devices and Wireless Mesh Networks for Collaborative Sensing

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***Abstract*— Wireless sensor networks have become one of the most productive and cost-effective ways of gathering data from the environment in a distributed and unattended fashion, and are considered as one of the key technologies of the twenty-first century in the field of pervasive systems, indeed contributing in the implementation of Internet-of-Things based ecosystems. However, the wide range of different hardware and software platforms, communication capabilities and data management techniques, makes the integration of heterogeneous technologies a must, so that the final success of the target deployment and the underlying service provision can be assured. In this way, the combination and interoperation of wearable technologies with wireless sensor networks is demonstrated in this work towards the implementation of urban collaborative sensing, particularly considering a twofold integration process: seamless connectivity among wireless mobile and deployable devices, as well as hardware-software embedded support for dynamic interaction with sensing/service capabilities.**

Keywords—Wearable devices, wireless sensor nodes, heterogeneous systems, localization, HW-SW co-design.

I. Introduction

Wireless Sensor Networks (WSN) are quickly becoming the most productive and cost-effective way of gathering data from the environment, and are considered one of the most important technologies of the twenty-first century in the field of pervasive systems. These networks consist of small, inexpensive and unattended devices that are deployed in a region of interest to sense parameters such as temperature, humidity or air quality. They are used for a wide range of applications such as dangerous environment monitoring, deployments in agriculture or the food industry, and even for security and surveillance systems.

Because of their scalable and inexpensive nature, wireless sensor networks are also ideal for Intelligent Transportation Systems, and are called to be the main infrastructures for this type of applications in the Smart Cities within the near future. With more and more devices becoming connected in the *Internet of Things* (IoT) ecosystem, the information gathered by these networks is becoming available to smart systems as well as personal phones or tablets, which is traduced in a wider range of end-to-end applications for wireless sensor networks, as the user can not only benefit from parameters that the network senses, but also interact with it in an easy and user-friendly way.

In addition to this, in the recent years the so called *wearable* technology has also broadened the possibilities of benefiting from distributed sensing. Similarly, as in Wireless Sensor Networks, wearable devices have nurtured themselves from the advancements in the capabilities of electronic devices and the development of better and more specific communication protocols towards the integration with IoT. These devices contain in a very small packaging an enormous processing capability, energy efficient power systems, and can usually manage Bluetooth or Wi-Fi communications. As the IoT technology is becoming more mature, the spectrum of diverse and heterogeneous hardware and software elements is also growing exponentially, and their proper integration is envisioned as an important challenge to be faced from different angles.

One of them is approaching the correlation among the distributed devices on one hand from the communication point of view, and on the other hand from the data and processing interconnection perspective. In the world of WSN the most extended communication standard is the IEEE 802.15.4, that defines the physical and MAC layers for Low Rate Wireless Personal Area Networks (LR-WPANs) that focus on low-cost, low-rate, ubiquitous communication between devices. Implementing this communication protocol on any smart device would allow a seamless communication with wireless sensor nodes, and if this device is also a wearable system the first technology access barrier is broken, as the user only has to carry the device as a day-to-day accessory.

Based on this, this work proposes the integration of one of these smart wearable devices with a modular HW/SW integration platform for Wireless Sensor Networks, developed to achieve a high degree of design adaptability and low level control of the sensor node. This combination creates a rich and powerful architecture that can be used for a wide variety of applications, and provides an innovative and attractive solution for the integration of WSN in the Internet of Things domain. With this, the main goal of the proposed system is to be implemented for location and detection applications as two preliminary use cases, and the target of this paper is to provide an overview of the proposed architecture, highlight its potential, as well as introduce some experimental characterizations towards implementing the collaborative sensing applications it is intended for.

The remainder of the paper is divided in the following sections: Section II presents an overview of the state of the art of the integration of WSN in the IoT ecosystem, previous works that merge smart devices and WSN, and the current state of localization algorithms for WSN. Sections III and IV introduce the general and technical aspects of the proposed architecture, whereas Section V exposes the obtained experimental results of this integration for distance estimation and service provision. Finally, conclusions and future work are highlighted.

II. Related Work

In the era of IoT and connectivity the society has been flooded with small, intelligent, and power-efficient wearable devices that are thought to be user-friendly, packed with features, and can connect to nearby devices or to cloud services far away. The potential of these new types of ubiquitous technologies lies precisely in their communication capabilities, where Bluetooth is the most used wireless communication standard for this family of devices, despite its nature limits the variety of applications that the device can partake in, and the services that it can offer. Expanding the communication capabilities of these wearable devices greatly enhances their possibilities. [1] and [2] explore using the IEEE 802.15.6 standard for Wireless Body Area Networks to monitor physical parameters, and propose approaches to deal with the challenges that the standard has.

In this IoT paradigm, WSN are changing the way data is gathered in a distributed, inexpensive and scalable manner. Connecting smart elements such as tablets, smartphones, or the aforementioned smart wearables to the internet opens up a wide new range of protocols and applications, as the ones presented in [3], where smartphones are used to implement a distributed, portable architecture to infer physical activity. In [4] the goal is also to monitor physical parameters, but this time using a wearable device and integrating it in a WSN, which collects environmental data. Using both datasets –one from the wearable and one from the wireless sensors- the network makes decisions concerning the performance of the sport practice and suggests the user a set of exercises. Also, a middleware is implemented to integrate the different hardware platforms: the wearable and the WSN nodes.

The integration of wearable devices with sensor devices moves away from the traditional uses of WSN concerning environmental data collection towards more dynamic, user-involved systems such as hazard detection systems for dangerous industries using wearable nodes like in [5], where a proprietary wearable node was developed for the application.

The system introduced in this work is similar to [5] from a Wearable-Wireless Sensor Network point of view, but this time the wearable system is not just another current node, but an intelligent IoT platform with the fundamental characteristics of a WSN node, an embedded Real Time Operating System, and a graphical user interface from which the network can be monitored and managed. This work studies the integration of this smart, wearable, inexpensive device with a modular HW/SW platform for WSN, resulting in a flexible, dynamic, and powerful architecture, with the goal of being used for localization and detection applications. The ultimate target is to provide a broad variety of services and collaborative applications, in which wireless sensors and wearable devices work in a coordinated manner to enhance the performance and usability of the deployed network.

In this way, locating a node in a WSN is an important research area within the field, as the data that the devices gather is useless if it comes without any localization information. For this task there are two families of methods: Range-free and Range based methods. Range-free methods use radio connectivity to communicate between nodes and infer their location. In range-free schemes, distance measurement and special hardware are not used (they work using the known distance between a series of reference points), which makes the problem of distance estimation disappear, but the methods require a high density of nodes and perform poorly in irregular networks. Some examples of these kinds of algorithms are DV-Hop [6] and APIT [7]. Range based methods on the other hand rely on distance estimation between the nodes using radio parameters, which sometimes can be unstable. RSSI is the most common metric used by range-based algorithms in WSN for determining the distance from one node to another.

There has been a lot of research in order to decide whether this parameter leads to an accurate estimation of distances between nodes. In [8] different algorithms that use RSSI for indoor localization are studied and the realization that more complex solutions are needed to achieve higher accuracy estimations is reached. In [9] the behavior of RSSI in ideal environments is studied and authors conclude that the metric is not reliable at long distances and in different directions. However, many models that use RSSI have been developed which lead to reasonable distance estimations, such as [10] or [11]. Both works use the Log Normal Shadowing Model (LNSM) in its standard form or with slight variations to determine the relation between RSSI and distance. In its most simple expression this relationship is described by the following equation:

$$RSSI = RSSI_{d_0} - 10\eta log\left(\frac{d}{d_0}\right) \quad (1)$$

where $RSSI_{d0}$ is the received signal strength at a reference distance d_0, and η is the path loss exponent, which represents the reduction of the power density of the signal as it travels through space.

The Link Quality Indicator (LQI) is the other parameter that has recently started to be used in this kind of networks for calculating distances. The reach of LQI raging techniques has been explored in [12] and promising results were obtained after a refinement process was made to raw LQI data. Techniques that use both of these metrics have already been explored in [13] and [14], which show that the use of both, RSSI and LQI, can lead to higher accuracy than those methods that rely exclusively on one of these parameters. This work proposes an approach similar to [13], using RSSI assisted by the LQI metric for improving distance estimations, but in this case LQI values are not used to smooth the RSSI curve, but to directly filter packets that have a high chance of presenting an

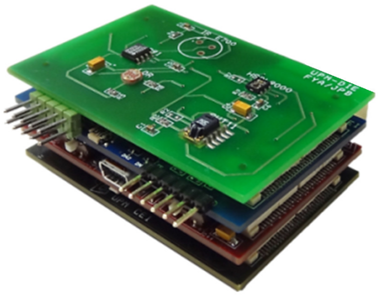

Figure 1. General view of a Cookie node, where the four different layers can be observed.

Figure 2. Hexiwear's main screen.

irregular RSSI value due to particular instability, so that the final prediction error is not penalized by transient deviations.

III. System Architecture

In this context the proposed system consists of a WSN HW/SW platform called *Cookies* [15, 16] and a smart wearable device: The *Hexiwear* [17].

Cookies is a modular, HW/SW integration platform for Wireless Sensor Networks, which consists of different independent layers that tackle the four fundamental aspects of the wireless sensor node hardware. The core of this platform lies in its modularity and flexibility that allows a high degree of adaptability to different application requirements, supported by a layer-based architecture composed of 4 main elements: processing, sensing, communications and power supply. Each layer can be seamless interconnected to the rest of the platform through vertical connectors that provide both mechanical and signal support to the sensor node. In line with this modularity, a complete set of software libraries has been developed as a framework for the low level control of the nodes, and application profiles have also been created for the management of the network, from user to application and application to node. A general view of a Cookie node is presented in Figure 1.

Hexiwear on the other hand is a device designed to combine the characteristics of a smart IoT wearable with those of a WSN node, and open source hardware and software to make it fully customizable. It has two energy efficient microcontrollers, where one acts as the core of the platform performing all the processing tasks, and the other one handles the wireless communications, a 96x96 pixel OLED screen, 6 haptic feedback buttons, and a wide variety of sensors which include an accelerometer, humidity and temperature sensors, and a heart rate sensor. The wireless communication stack is IEEE 802.15.4 compliant, making it ideal for WSN applications, where this is the de-facto communications standard, as mentioned before. Also, the main processor supports the inclusion of a Real Time Operating System that handles all the different tasks in separate processing threads and optimizes the use of the hardware resources. Fig. 2 presents a general view of the Hexiwear device.

By merging these two prototyping HW/SW platforms the modularity and flexibility of the Cookies is combined with the potential of Hexiwear, with its GUI and embedded OS, its two processing cores, and customization capabilities, to achieve an architecture that provides an enhanced support for a wide range of application contexts, and defines a multi-platform development framework for the IoT ecosystem.

Fig. 3 shows an overview of the low level architecture of this Wearable/WSN platform with its different modules: The main and slave processor of the Hexiwear, the communication module of the Cookie, and both components of the processing layer: The low-power microcontroller and the FPGA element.

From the user interface of the Hexiwear, different network aspects are managed such as starting the network, and receiving messages from or sending to Cookie nodes. The main processing core in Hexiwear registers the user interaction and sends the corresponding message to the IEEE 802.15.4 uC that then transmits it over the network. Both microcontrollers communicate via UART to transmit information from user to network or network to user. The associated control and processing tasks are triggered by using a thread-based structure through the embedded OS, to achieve a highly efficient management of the hardware resources of the device. The information sent from the top level application travels wirelessly to the Cookie, which is received by the IEEE 802.15.4 module in the communication layer, and shared with the uC in the processing layer via UART, which then processes it and starts the desired collaborative actions. This processing layer also has two separate processing cores as in the Hexiwear, but in case of the Cookie, one of them is an FPGA that handles more demanding hardware tasks such as digital signal processing, the management of protocols to control digital sensors, and the exchange of co-processing information with the uC.

IV. System implementation

This section gives a more detailed description of the architecture proposed in the previous section. The main processor embedded in the Hexiwear is the Kinetis MK64 [18] from Freescale, which features low power capabilities and an optimized integration in an ultra-small packaging. This MCU includes a 32-bit ARM Cortex-M4 Processor, and fully supports the Real Time Operating system FreeRTOS [19]. By using this RTOS, tasks such as collecting data from the sensors, displaying information on the screen, or the battery management can be controlled in different threads, optimizing

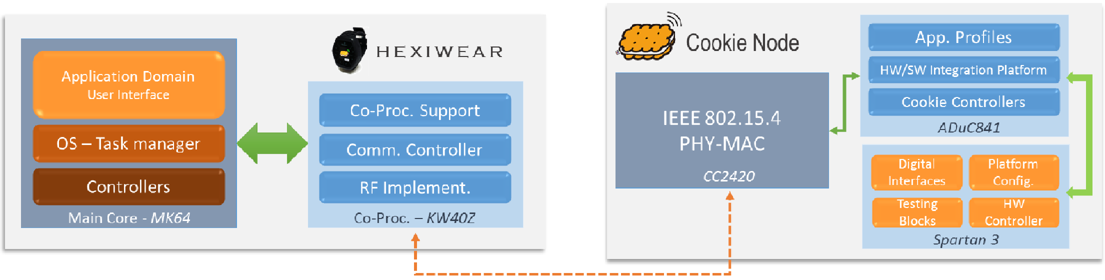

Figure 3. General Architecture of the proposed heterogeneous platform for IoT.

the use of the system. In the particular case of the proposed architecture, one of these threads is used to interact with the IEEE 802.15.4 MCU, separating the communication process from the rest of the functions of the uC. The MCU that implements the communication capabilities is the Kinetis KW40Z [20], also from Freescale, with Bluetooth Low Energy (BLE) and IEEE 802.15.4 RF connectivity for portable, extremely low-power embedded systems. The KW40Z integrates a 2.4 GHz transceiver, and an ARM Cortex-M0 CPU. The communication between both uCs is done via UART, by transmitting predefined packets that can be customized according to the target application.

On the Cookie's side, the processing layer represents the core of the modular platform, as it is in charge of controlling the rest of the involved layers, collecting environmental data using the sensors, managing the network connections and transmitting information through the WSN using the wireless capabilities of the communication layer, and configuring the power-down mode of the node. The microcontroller is an ADuC841 from Analog Devices [21] which integrates an optimized single-cycle 20MHz 8 bit MCU. The other processing element, the FPGA, is a Spartan 3 from Xilinx [22] with 200000 equivalent gates. On the other hand, the Cookie node includes a communication layer based on the CC2420 module from Texas Instruments [23], which implements the PHY and MAC layers of the IEEE 802.15.4 standard.

Fig. 4 shows a general view of both the Hexiwear and the Cookie platform that composed the proposed heterogeneous systems for IoT applications.

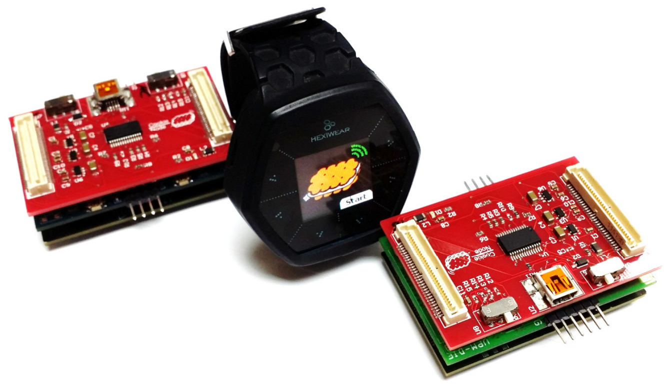

Figure 4. Hexiwear device with two Cookie nodes.

V. Experimental Results of the Integration

A. *Platform compatiblity*

The first task of this integration process was related to establishing the wireless connection of the Hexiwear and the Cookie nodes through their corresponding communication implementations. Despite the fact that both platforms are compliant with the IEEE 802.15.4, the heterogeneity of the architecture did not guarantee a straightforward communication between them, as sometimes devices that can support the standard are not able to successfully communicate because of actual implementation mismatches. Freescale provides a series of libraries for implementing the functions of the IEEE 802.15.4 standard, and a SDK with examples of applications that use the provided stack. With these guidelines the firmware of the KW40Z was modified, taking care to not alter any of the functions that Hexiwear's main MCU depends on for its correct functioning. The Hexiwear was then programmed to start a Personal Area Network (PAN), wait for incoming messages from devices in that PAN and print those messages in the OLED display. Also, a Cookie node was prepared to send messages to the Hexiwear and via an USB connection to a PC, display the control and acknowledge packets when those messages successfully got to the destination point. This first stage of the integration process ended up with a successful communication between both platforms, then obtaining a package exchanging scheme among the mobile and the deployed sensor nodes.

B. *RSSI Measurements between heterogeneous devices*

After successfully communicating the devices, as the final goal of this system is to be used for localization and detection applications, a series of experiments were conducted to study the relationship between RSSI and distance in the communication between these two heterogeneous platforms, as well as explore ways to improve this relationship. A Cookie node and the Hexiwear were placed in clear line of sight, one meter above from the ground, in an indoor environment, and at the beginning of the experiment, one meter away from each other. The Cookie sent messages to the Hexiwear and the values of RSSI and LQI were displayed on the screen of the device. The Hexiwear then sent a message to the Cookie with the RSSI and LQI values measured, to store this information in a terminal Log. Fifty messages were sent each time, and then the distance was increased in steps of one meter, up to a maximum distance between the devices of ten meters, to

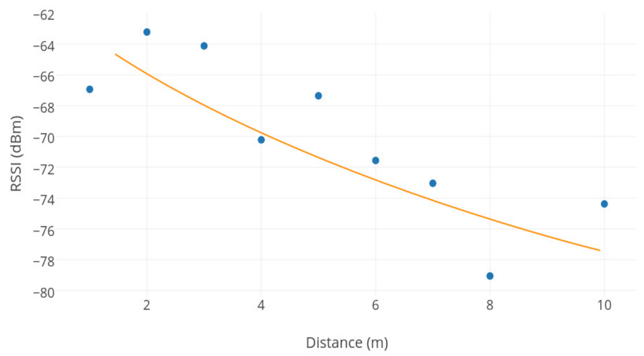

Figure 5. RSSI vs. distance at 0 dBm Tx power with Hexiwear.

provide a dataset of more than one thousand RSSI and LQI samples. Fig. 5 shows a graph of the behavior of RSSI as distance increases for a Tx power level of 0 dBm and the logarithmic trend. The values shown are the mean of the fifty RSSI values collected for each distance.

From this graph it can be seen that the degradation tendency that is reported by the experiment is similar to the theoretical outcomes. However, it can also be observed that there are certain inconsistencies in the RSSI values that drive the need to enhance the model and increase its accuracy so that the algorithms that use these parameters can achieve a higher degree of precision.

C. Errors in distance estimation

An RSSI to distance conversion was performed for short distances (focused on indoor scenarios) to quantify the errors between the distances predicted by the model and the actual real distances. For this, the Log-Normal Shadowing model introduced in section II was used. From equation (1) the distance d can be obtained as:

$$d = d_0 . 10^{(RSSI_{d_0} - RSSI)/10\eta} \quad (2)$$

The parameter η was fixed at 1.8, value that is commonly used for indoor environments. The RSSI was measured multiple times at a reference distance of one meter and the mean value obtained was -66 dBm. The Hexiwear was then set up to send a message to a Cookie node upon pressing one of the haptic buttons of the device. After receiving ten messages the Cookie node averaged the RSSI of all of them, calculated the distance to the device and displayed it in a terminal instance. This process was repeated ten times from one up to eight meters and the distances obtained after averaging all of the results are shown in Table 1.

It can be seen that the error in distance estimation increases as the devices move further away from each other. More precise estimations could be obtained by a better characterization of the environment or by implementing an improved model according to the behavior of the communication between both platforms, as proposed in the following section.

Table 1. Distances obtained by the LNSM.

Real distance (m)	1	2	3	4	5	6	7	8
Estimated distance (m)	1,18	1,78	2,44	4,78	3,91	7,45	8,68	5,91

Table 2. Distances obtained by the LNSM using the LQI filter.

Real distance (m)	1	2	3	4	5	6	7	8
Estimated distance (m)	1,09	1,91	2,77	4,41	4,11	7,09	8,35	9,86

D. LQI packet filter

During the data collection process, it was observed that certain packets with low LQI values produced RSSI measurements that were inconsistent with the previous values measured at the same distance. For this, it was decided to implement an LQI packet filter for distance estimations, so that packets that carry a low LQI value are not used in the distance calculation process. By using this filter different distances were calculated again using the LNSM. Table 2 shows the results of using the LQI filter. Fig. 6 compares the errors from the previous measurements using pure RSSI data, and the new measurements based on the LQI filter from 1 up to 8 meters.

This graph shows that the proposed filter reduces the error in the distance estimations by discarding packets with low LQI values that have particular deviations in RSSI values associated to them. Future works will be conducted to confirm this correlation of poor LQI and inconsistent RSSI values, and in those cases where the characterization produces the encountered deviation, apply the filter to increase the accuracy in localization algorithms.

E. The use of the LQI filter for localization and service provision

The desire of obtaining more precise distance calculations lies in the principle that most localization algorithms rely on this distance for a precise estimation of the node's position. The errors in the distance variables calculated can lead to even bigger errors in the triangulation algorithms that compute such distances, or even in the algorithm not working at all, as the resolution of the equation systems that these algorithms use might not exist if the distance variables are very far off their real values. Fig. 7 shows a diagram of the implementation of a triangulation algorithm based on the deployment of 3 Cookie nodes with known positions and a mobile Hexiwear device. The proposed LQI Filter, apart from increasing the accuracy of such algorithms could also be used in a service-oriented manner: Those communications that frequently report low LQI values could be discarded and closed until the user of the Hexiwear device decides to reopen them using the user interface of the device. This approach could increase the energy efficiency of the network, improve the data traffic

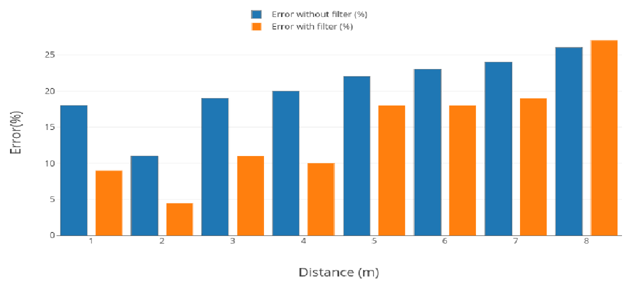

Figure 6. Errors (%) obtained by the LNSM for different distances with and without the LQI filter, from 1 up to 8 meters.

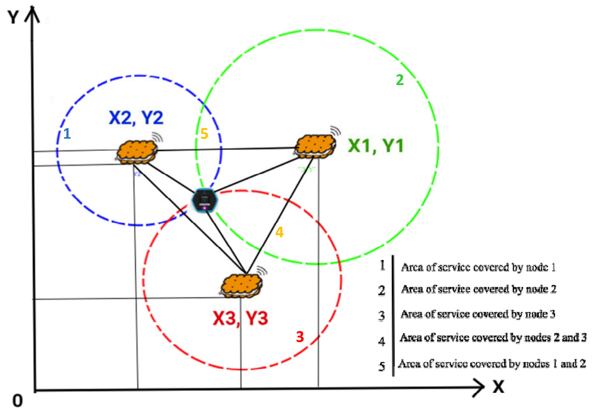

Figure 7. Triangulation algorithm to estimate the coordinates of the Hexiwear device using 3 Cookie nodes, and service provision.

patterns, and stop unnecessary messages from being sent. It also highlights the collaborative approach of the network, as the mobile device using received LQI values could decide which services it will listen to, interacting with the rest of the nodes in a dynamic and user-involved fashion. Fig. 7 also portraits the same deployment but from a service-oriented point of view, instead of from a localization perspective. In this image, the different areas of service for each of the Cookie nodes are shown, as well as the overlapping of several of these areas, to highlight the collaborative scenarios that could be covered depending on the positioning of the nodes, and the mobility of Hexiwear.

VI. CONCLUSIONS AND FUTURE WORK

Merging smart wearable devices with sensor networks is a huge step towards globalizing the use of WSN technology and integrating them in the IoT ecosystem. This integration multiplies the range of applications that WSN can be used for, and puts an unlimited amount of services at the fingertips of the user. For this fusion to work at its best, the wearable devices should be compliant with the communication standards of WSN and IoT. If this happens, the smart device can act both, as a node in the network and as a gateway to another platform. This work puts this idea into practice, integrating a wearable device with such communication capabilities with a powerful and flexible platform for WSN. As this integration has been successful, future work will be focused towards implementing applications that make use of this rich architecture with new models for estimating node-to-node distance in localization and detection techniques and providing more diverse collaborative services.

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