

# Smart-Helmet development for Ecological Field Research Applications

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**Abstract.** *Forest inventory and management are important topics to enhance environmental protection initiatives and policies. Thus, sampling processes inside the forest environment are normally manual and limited. These conditions nurture an increasing need for novel solutions to enhance environmental perception, especially in ground-sampling processes. In this work, we present a new solution to augment environmental perception. The proposed appliance is a wearable embedded system based on a helmet and projected to acquire environmental data. It also allows the development of new applications to expand the researcher reality perception.*

## 1. Introduction

Forests are crucial environments in terms of ecosystems and biodiversity [Brandt et al. 2016]. Thus, there is also an economic interest in forest areas and products. In this context, it is essential to increase the knowledge from the forest areas. This kind of information is a tool to enforce conservation efforts.

According to White et al. [White et al. 2016], the increasing forest management and inventory requirements raise the demand for new technology acquirement techniques. They affirm that most of the forest management technologies are satellite or aerial scanning over forests. Even measurements using devices such as LIDAR are remote or airborne [Jeronimo et al. 2018, San Juan and Domingo-Santos 2018, Fedrigo et al. 2018, Sankey et al. 2017, Humagain et al. 2018]. Ground sampling techniques are limited and often involve manual processes [Asner et al. 2015].

Moreover, many forest research techniques expose the researcher to dangerous activities. Mazzocchi et al. [Mazzocchi et al. 2015] for example, specifically address the tree climbing danger issue. They affirm that tree climbing activities expose the climber to a danger of falling from big heights. Often, a forest-environment researcher must climb trees upwards and downward during canopy studies [Ribeiro et al. 2011], in trees with unknown conditions.

Within this context, we understand that one way to fulfill this technology and safety demands is expanding the perception of researchers involved in ground environmental variables sampling. In order to achieve an augmented knowledge from the environment, new proposed devices need to be non-obtrusive, portable, lightweight and capable of acquiring environmental data. Also, technology supports faster and more efficient work, leading to lower danger exposure times. As we discuss in Section 3, these requirements are ground features from wearable embedded systems.

Therefore, in this work, we present the development process of a novel wearable solution to increase environmental perception in forest field research. This process starts at the architecture proposal, with sensing nodes based on the *Internet of Things* concept. After that, we present a developed prototype. Finally, we developed an application to allow an expanded perception of the environment.

This text starts with a theoretical review and related work presentation in Section 2. Then, we present the main system requirements in Section 3. The proposed architecture for this system is discussed in Section 4, where we also present the developed prototype in Section 4.1. After this, we discuss the developed application on Section 5, where we present a case study where our tool can be applied (Subsection 5.1) and the data fusion process (Subsection 5.2). Finally, we analyze our results and conclusions in Section 6.

## 2. Theoretical Reference and Related Work

According to West et al. [West et al. 2015], there is a trend to develop novel devices using data fusion and Augmented Reality (AR), Virtual Reality (VR) and Mixed Reality (MR). This trend is due to the increasing ubiquity of data-producing devices in consumer and industrial applications.

A tool to augment the perception of the environment is the Wireless Body-Area Network (WBAN) architecture. Ullah et al. [Ullah et al. 2012] present WBANs as a group of low-power and lightweight sensor nodes. A WBAN system can be used to enhance the human perception of the surrounding environment.

In the context of Smart-Helmets, some of the applications already explored are road accident detection [Chandran et al. 2016, Uma et al. 2018], military appliances [Jo et al. 2017], disaster rescue workers safety [Jeong et al. 2018], industry [Roja and Srihari 2018, Harshitha et al. 2018] and construction sites [Pirkl et al. 2016]. Although there are many proposed helmets, no other authors present a novel smart helmet developed for field research in ecology.

What these designs and other IoT-based Smart-Helmets [Deva et al. 2018, Magno et al. 2016, Jose et al. 2017] have in common is that they design the architecture as a single *IoT* device or node. Architectures with only one computer or micro-controller responsible for acquiring sensor data, processing and streaming this data may have performance issues when overloaded with multiple tasks.

A possible outcome for this problem is turning an embedded node into a local distributed node network. According to Calvaresi et al. [Calvaresi et al. 2017], these techniques originated from the Internet of Things (IoT) and Cyber-Physical Systems (CPS) and have been applied to develop intelligent and pervasive systems. In this kind of architecture, the acquisition, pre-processing and streaming tasks are divided between different

nodes.

### 3. System Requirements

Wearable Systems are Embedded Systems. Therefore, the core requirements for every wearable system are the same as the general embedded systems requirements: Energy, Robustness, Timing and Communication [Hansen 2017]. Also, they have some further requirements due to their nature. They need to be comfortable and easy to use [Rhodes 1997]. Also, they must augment reality through context-awareness [Billinghurst and Starner 1999].

In order to understand how these restraints apply to our desired context, we performed several interviews with the target users from the technology. From their knowledge, we estimated the energetic autonomy and robustness requirements in a qualitative or semi-quantitative form. The Communication and Synchronization requirements come from the proposed architecture features.

As this system needs to be taken into the field, it needs to work for hours without needing battery recharge or replacement. It needs to be robust enough to take hits from branches and falling seeds or nuts. As we propose a distributed system in a WBAN-Environment, both systems need to communicate with an application, working as web server nodes. Finally, the communication needs to be efficient to stream the data through this local network.

### 4. Architecture and Design Overview

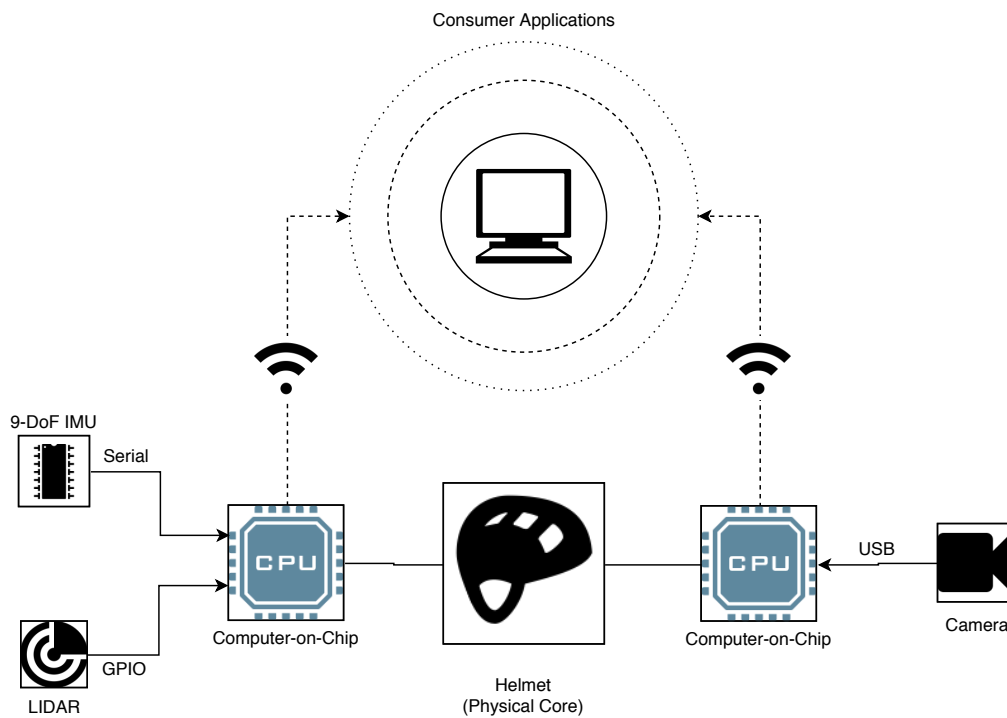
The proposed solution works upon a wearable distributed system working in a Wireless Body-Area Network (WBAN). This system is projected to allow information extraction through Data Fusion, Image Processing and Computer Vision. Figure 1 presents the proposed architecture for this system.

The first aspect of this system is the physical core. As we propose a wearable system, it needs to be an unobtrusive system [Bonato 2003]. Therefore, we built the system over equipment which lets the user hands-free. The physical core which presents the best option for the wearable and research requirements is a helmet. In Silva et al. [Silva et al. 2019], we discussed some of the appliance constraints. Especially, we estimated the energetic requirements and consumption for such solution.

The following aspect is the construction of the *IoT*-based sensor nodes. Each node is a Computer-on-Chip capable of reading single or multiple sensor data, pre-processing this data and casting it over a WBAN. The chosen sensors to augment perception to the environment are a laser radar (LIDAR), a 9-Degree-of-Freedom Inertial Measurement Unit (9DoF IMU), and a regular camera.

The Computer-on-Chip must be able to read the required I/O interfaces from each sensor. Also, it must be able to establish a wireless connection in the local body-area. As wearable systems have strong energy constraints, the Computer-on-Chip must carry a low-power processor. Thus, ARM-Based computer-on-chips are adequate solutions for this purpose.

In general, the candidate devices to perform as core applications for this system are ARM-based Computer-on-Chips, with multiple different I/O interfaces to attach the



**Figure 1. Proposed Architecture**

required sensors, and a network card capable of streaming the data through a local wireless connection.

We chose the Wi-Fi network standard<sup>1</sup> (IEEE 802.11) as WBAN-interface. This choice was based on the ease to create web server solutions. Also, it was based in the broader band capability to guarantee the connection quality, especially when dealing with camera streaming.

Within this network, each sensor node operates as a local web server. Any application built should be able to request the sensor data from each node over the WBAN. The application performs a data fusion algorithm and augments reality.

#### 4.1. Prototype Development

In order to test features from this proposed architecture, we built a prototype version of the solution. This model contains all previously introduced elements, with the required sensor nodes to acquire the environmental data. This information feeds a data fusion algorithm and augments reality in an external application. Figure 2 presents the developed system prototype for this solution.

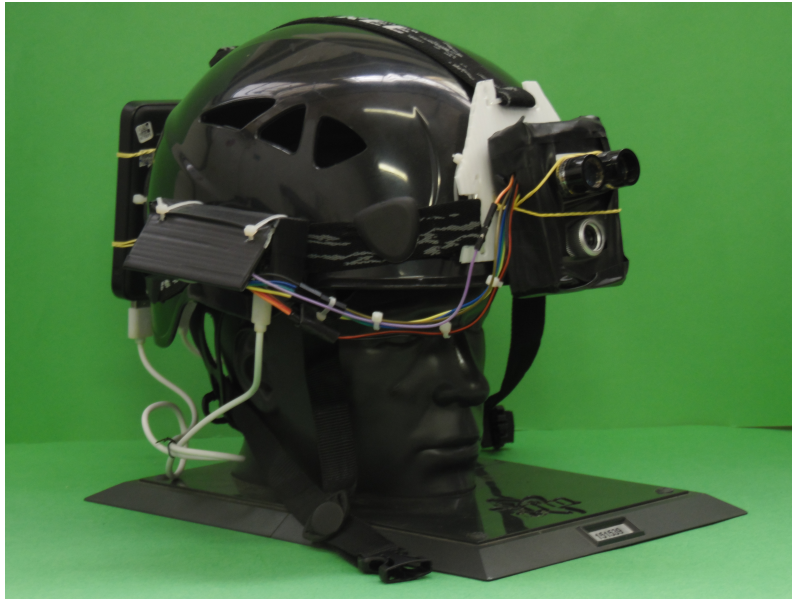
The sensors used in the first node are a LIDAR LITE V1<sup>2</sup> and a 9-DoF BNO055 module<sup>3</sup> for orientation. The second node is connected to a regular USB camera.

The LIDAR data is acquired monitoring its PWM step size output. According to

<sup>1</sup><http://www.ieee802.org/11/>

<sup>2</sup><https://cdn.sparkfun.com/datasheets/Sensors/Proximity/LIDAR-Lite-Data-Sheet.pdf>

<sup>3</sup><https://cdn-learn.adafruit.com/downloads/pdf/adafruit-bno055-absolute-orientation-sensor.pdf>



**Figure 2. System Prototype**

the device manual, this sensor is able to measure distances up to 30m, with a  $\pm 2,5$ cm uncertainty. The system monitors the step size using a general-purpose GPIO pin and the internal clock, which can raise the measurement variance. In order to partially overcome this problem, the practiced distance is a moving mean of the last four measurements. This technique helps to filter random variations caused by system task preemption.

The BNO055 is capable of offering different information to the user. It communicates using serial pins. This sensor measures absolute orientations using quaternions or Euler vectors. Also, if desired, it offers also information about angular velocity, accelerations, magnetic field, gravity vectors, and temperature.

The USB camera is a regular camera, transmitted using a network stream. As this task is computationally demanding and the computer modules have low-power and low-performance embedded processors, we used a single node dedicated only to this streaming.

We used Raspberry Pi Zero W as the Computer-on-Chip modules to host the sensor nodes. These are low-cost and small-sized Computer-on-Chips. The CPU in this module is a single-core ARM11 processor, with up to 1GHz clock frequency. Its network card supports Wireless 802.11n connection and Bluetooth LE. This card can be powered using a 5V regular power bank using a micro-USB power input<sup>4</sup>.

The whole solution stands over a regular climbing helmet. This model of helmet is indicated as safety equipment to dangerous activities in nature, such as climbing.

## **5. Application Development**

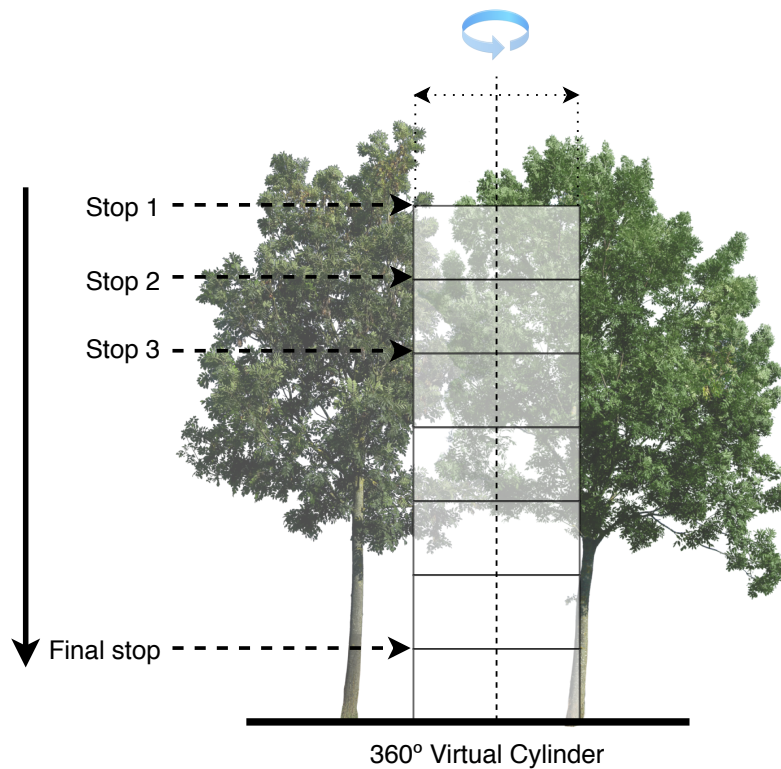
In the previous Sections, we proposed the architecture of a multi-nodal wearable system. Section 4 presents the proposed architecture. In Subsection 4.1, we presented a prototype with the capabilities to connect to a Wireless Network, constituting a Wireless Body Area

<sup>4</sup><https://www.raspberrypi.org/magpi/pi-zero-w/>

Network. The next step was building an application based on a data extraction process in ecology.

### 5.1. Case-Study

We chose a canopy ecology measurement process as our forest management case-study application. This process is named the *Pin-Cylinder Transect Method* [Pontes Ribeiro and Basset 2007, Ribeiro et al. 2011]. Figure 3 presents an illustration of the *Pin-Cylinder Transect Method*.



**Figure 3. Pin-Cylinder Transect Illustration**

In this method, a researcher manually samples leaves and galls in transects within a volumetric space of one-meter diameter from the upper canopy to a three-meter height above the ground.

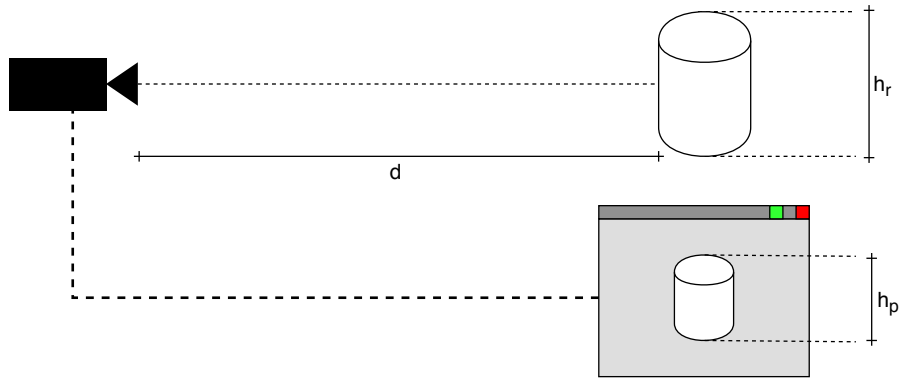
This measurement is performed climbing down the trees, which naturally requires climbing up also. Within this scenario, the comfort and free use of hands are essential aspects of the safety and success of the research. Therefore, wearable solutions present adequate background requirements to support this task.

The objective of this model application is making a virtual visualization of the transect. The sensors data must be fused with the image data to create this kind of visualization.

### 5.2. Data Fusion

In order to create our data fusion algorithm, we modeled a mathematical relation between the real height of an object and the virtual height in an acquired image. According to Hall

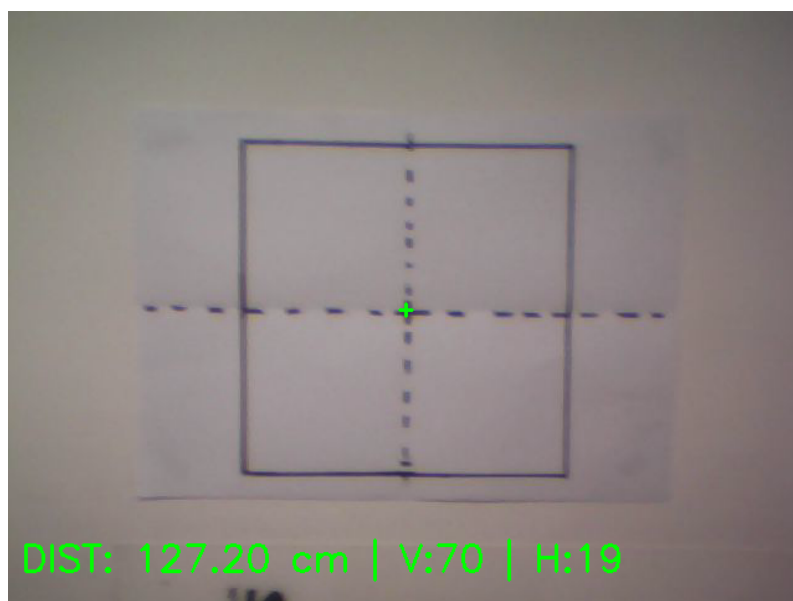
and Llinas [Hall and Llinas 1997], data fusion combines the data from multiple sensors and previous related information to increase the application perception. Figure 4 presents the variables used in the data fusion algorithm.



**Figure 4. Variables used in data fusion algorithm**

This process describes how the real heights ( $h_r$ ) relate to pixel heights ( $h_p$ ) in an acquired image from a camera located at a distance ( $d$ ) from the object. In other words, we seek to find out what is the pixel/cm ratio based on the distance from the camera to an object. This distance is known given the LIDAR sensor data.

In order to search for a mathematical law to represent this relation, we acquired the data from the camera in a 40cm x 40cm square at the wall together with the distance sensor. Figure 14 presents the acquired frame displaying all the data. We measured this distance for 19 different points and expected to extract a mathematical model which relates the pixel/cm ratio to the distance value.



**Figure 5. Calibration Square**

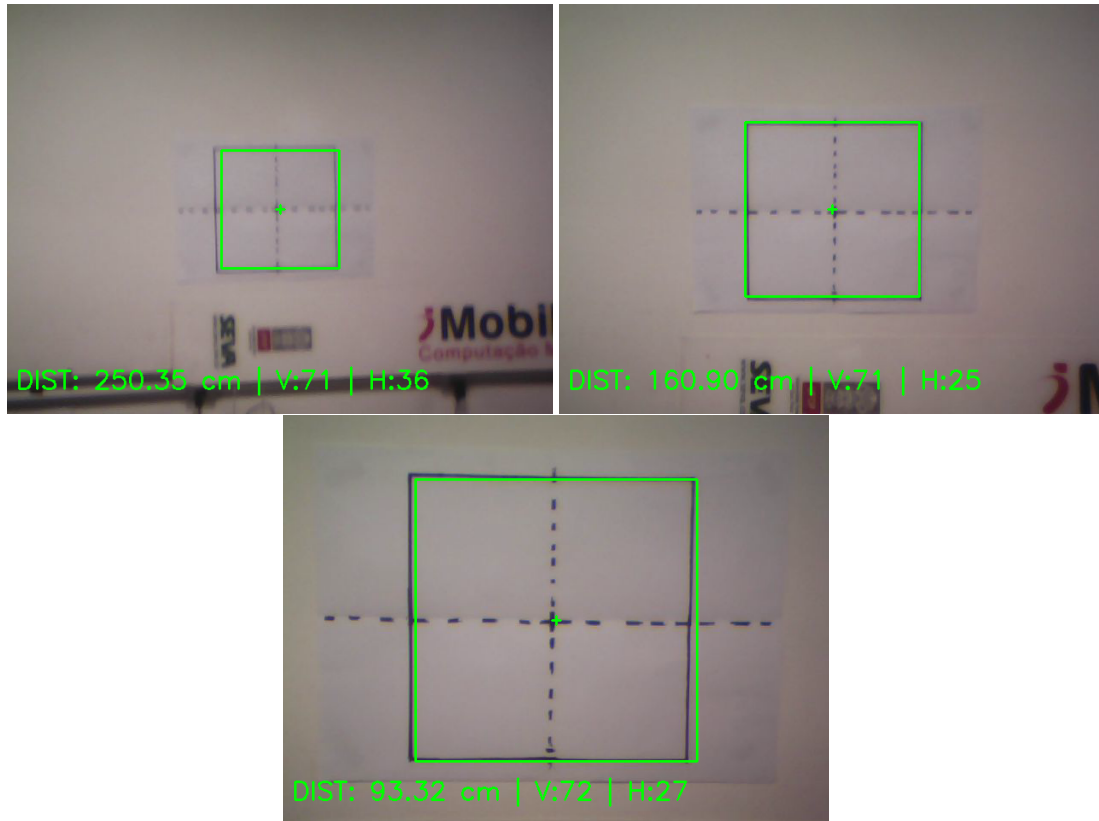
We searched to find a function which describes the pixel/cm ratio ( $R(d)$ ) in terms of the distance ( $d$ ) value. After finding candidate functions to perform this task, we tested them drawing a virtual square which should cover the real one. At first, we considered the hypothesis of a linear ratio. The linear function which best represents this relationship is:

$$R(d) = -0,036.d + 12,04 \quad (1)$$

With a coefficient of determination  $R^2 = 0,92$ . Although the regression found a potentially good result, the application using this adjustment misbehaved, especially when the distance increased or decreased too much. Therefore, we inspected the scatter plot and searched for a power regression where this relationship would be represented with a negative power function. The function which best represents this relationship is:

$$R(d) = 435,7.d^{-8,874} \quad (2)$$

With a coefficient of determination  $R^2 = 0,97$ . This relation presented potentially better behavior given its coefficient of determination. This potential turned into adequate behavior when used in the application for every distance tested, even in higher or lower distances. Figure 6 shows the virtual squared covering the calibration match for different distance values.



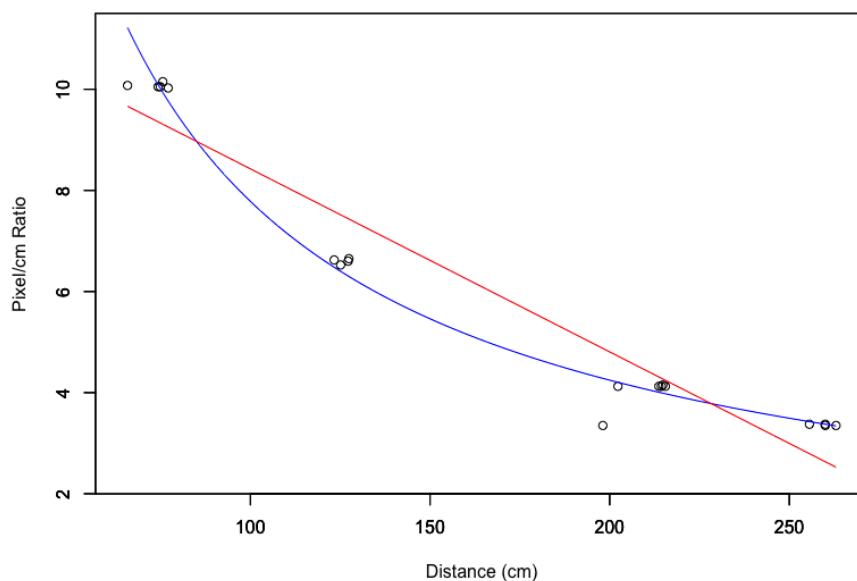
**Figure 6. Data-Fusion Application**

The data fusion process presented a good performance for different distance values, both from quantitative and qualitative evaluation methods. Therefore, the power fit



represents a suitable model to relate the pixel/cm ratio in terms of the distance. Figure 7 presents a comparison between both the candidate functions.

Within this figure, the black spots represent the original sampled values. The red line presents the resulting linear fit function. The blue line presents the resulting function for the power fit. Here, it is possible to observe how the linear regression model would mismatch values, while the approximations using a power regression are good representations of this model.



**Figure 7. Regression Models**

After completing this stage, we successfully built an application capable of placing virtual objects in the real world based on the data fusion of different sensors as a result of the proposed work. This makes our application capable of recognizing the transects in the tree canopy based on the sensors data, achieving reality augmentation. The images from the canopy are available to a further laboratory analysis, where the researchers can sample the leaves and review previous work in a safer environment.

## **6. Results and Conclusions**

In this paper, we presented a proposed architecture for a smart-helmet created to perform studies in ecology. We also described how we assembled a prototype with all the required elements from the proposed architecture. Finally, we presented an application developed as a concept-proof for this solution. We used a Canopy Ecology forest management process as our case study, achieving the desired results, with a reality augmentation application using a data-fusion algorithm.

Ecology field research usually requires free use of hands, comfortable, easy-operating and portable tools. These requirements are fundamental features in wearable systems. Therefore, we proposed a wearable solution to help researchers perform tasks in this context.

The proposed architecture works with IoT-based sensor nodes, distributed in a WBAN network environment. This provides sensor and image data to a client application, which can extract and present information through Data Fusion and Computer Vision. The network infrastructure uses existent wireless protocols, such as Wi-Fi.

Finally, we created an application designed for a case-study. The application should provide a virtual vision from a definite surface area in the real world based on the sensor data fusion. Our algorithm was calibrated using previously acquired data from calibration tests. The application was capable of placing this virtual transect area in the corresponding place to the image.

This prototype validates the elements proposed on the scope of this paper. Nonetheless, the solution requires improvements to be taken into field. This version bears partially exposed wires and electronics, which can be harmed in a true forest canopy climb. Also, this study doesn't cover final user experience aspects, which are important to the device adoption as a product.

Therefore, the next steps to this work are creating a better reality augmentation algorithm considering also the data acquired from the IMU sensor. Also, a further enhancement to this system is applying stronger Computer Vision algorithms to perform automatic counting, using convolutional neural networks. Another possible further step to this work is performing a user experience analysis based on a pilot application for the leaf counting process.

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