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Article Title: Fine Time Measurement for the Internet of Things: A Practical Approach Using ESP32

Fine Time Measurement for the Internet of Things: A Practical Approach Using ESP32

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ABSTRACT

In the world of Internet of Things (IoT), obtaining the physical location of devices has always been a task of great interest for developing increasingly complex location-based services (LBS). That is why in recent years wireless communication standards have been incorporating new additions focused on providing localization mechanisms to technologies widely used in the IoT world, such as Wi-Fi or Bluetooth. In particular, the IEEE 802.11-2016 Wi-Fi standard introduced ranging estimation between two devices through the so-called fine time measurement (FTM) protocol, defined by the IEEE 802.11mc. FTM is not yet widespread in the IoT field, but commercial modules capable of offering this functionality at a reasonable price are starting to appear. In early 2021, the most widespread system on a chip (SOC) family among IoT devices, the ESP32-XX series, added support for this Wi-Fi standard, enabling, for the first time, the use of a standard designed for location-based systems. This article analyzes the performance of this FTM implementation by carrying out and studying several measurement campaigns in different indoor and outdoor scenarios. Additionally, this work proposes an alternative real-time implementation for distance estimation inside the ESP32 using an approach based on machine learning. Such an implementation is successfully validated in a scenario totally different than those considered for the training and test sets. Finally, both the measurement sets and the developed software are available to the scientific community.

1 Introduction

The global pandemic of COVID-19 demonstrated the important need not only to know all kinds of data, such as CO2 rates or occupancy levels but also to know the physical location of the sensors that produce them. The location of sensors within the aforementioned scenarios often becomes challenging due to the following reasons [3]. 1) In many occasions, global navigation satellite system (GNSSs) are not an option because the sensors are located in scenarios (inside buildings, urban canyons, etc.) where the performance of such systems is very poor or they simply do not work. And even in open areas where these systems could work, the cost of adding such capabilities to the sensors would be too high to be viable for large-scale deployments. 2) The complexity of the scenarios in which IoT sensors are placed

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often makes their localization very difficult. This is especially true when radio frequency (RF) technologies are employed. Phenomena such as interference or non-line of sight (NLOS) propagation yield significant errors in position estimates. 3) Typical deployments in the IoT world require the installation of many sensors, which means that the individual cost of each unit must also be very low in order not to exceed the project budget. Therefore, in certain cases, some localization technologies are excluded in advance for budget reasons, even if they perform satisfactorily. There are, therefore, numerous technological alternatives to achieve position estimation within the IoT world, each with its own particular characteristics in terms of accuracy level, deployment and maintenance costs, reliability, or operational requirements. Among the various localization systems available [4]–[6], those based on RF are some of the most popular. Their basic operation consists of emitting and receiving some type of waveform with certain characteristics and extracting from this transmission some physical parameters that allow for estimating the position of the emitter or receiver

2 Related Work

Many task allocation problems have been studied for MCS in recent years. At the beginning, researchers studied the single task allocation problem. In general, all the aforementioned works showed that the Wi-Fi FTM technology can provide good results in terms of accuracy in outdoor environments without obstacles, but many problems arise in indoor environments. In these complex scenarios, the studies showed that, without a minimum calibration or optimization of each device, the results may lead to errors of tens of meters. In all the studies, Wi-Fi cards or smartphones were used as initiating devices, hence none of them addressed the problem of energy consumption or cost when describing the technology. In this article, we will analyze whether the ESP32-S2 offers results with similar accuracy to those obtained in previous works, but also take into account its characteristics as a device to be used in IoT environments.

3 System Overview

1) Indoor Scenario: The CITIC showroom (see Fig. 1) at the University of A Coruña, Spain, was selected as an indoor environment. This is a space dedicated to the dissemination of the research activities carried out in the center. It is a room with many obstacles inside and surrounded by sources of interference such as other Wi-Fi networks (more than 7 were detected with a high signal level from inside the room) coexisting with ZigBee sensor networks and Bluetooth devices. The dimensions of the room are 12 m long and 6 m wide, with a height of 3.2 m

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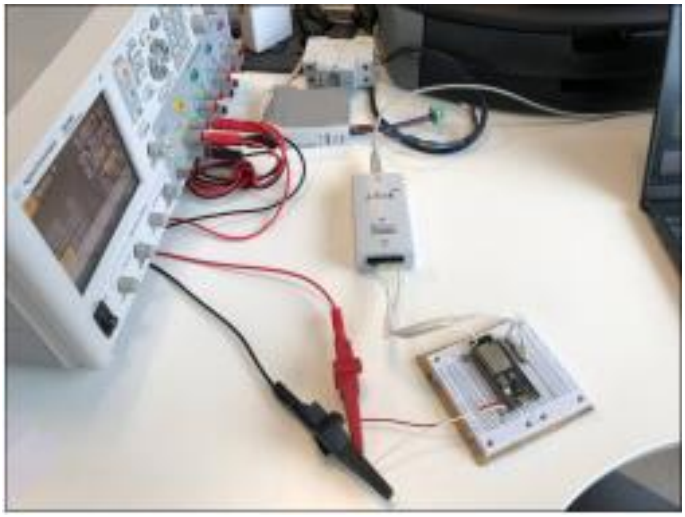


Figure 1: *ESP32-S2 current consumption measurement setup*.

2) Outdoor Scenario: In order to obtain more information about the capabilities of the ESP32-S2 module for ranging operations with the Wi-Fi FTM protocol, another measurement campaign was performed in an outdoor environment. In this way, we tried to minimize the possible effect of interference and multipath typically found in indoor scenarios. In fact, in this scenario, not a single nearby Wi-Fi network was detected that could be a source of interferences. To carry out the measurements, we selected an area of the campus at the University of A Coruña away from the buildings. Only two modules were used in the experiment, one acting as a tag and the other as a beacon. They were mounted on tripods and placed one in front of the other at the same height (1.75 m). The measurements were taken during 120 s at distances varying from 1 to 20 m, at 1 m intervals. Two different measurement campaigns were performed, one with the modules configured with a bandwidth of 20 MHz, and the other with a bandwidth of 40 MHz. Fig. 3 shows a picture of the outdoor measurement scenario.

4 Description of the ML Algorithms

The considered ML algorithms are described below. All of them are classical algorithms in the literature, and they are widely used in regression problems. 1) Regression Trees: This is an intuitive technique based on binary search trees applied to the regression problem [42]. The idea of these algorithms is to associate homogeneous input sets with the same output. The minimum leaf size is a fundamental parameter in this type of algorithms since, depending on its value, the trees can easily tend to over fitting. In the case presented in this work, the regression tree had a minimum leaf size equal to four. 2) SVM: This is another classic ML algorithm originally described in [43] that can be used in both classification and regression problems [44]. Among the hyper parameters that can be configured in this algorithm, the main one is the type of kernel used to map the input elements in the n-

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dimensional feature space in which the regression process is applied. In the implementation considered in this work, a Gaussian kernel was chosen with the form k xi, xj= exp − xi − xj 2 (2) being xi, xj ∈ Rn with n = 2 since the input vectors consider two features in our case. 3) GP: This is a generalization of the Gaussian probability distribution in which the behavior of a function is described. Using this idea, regression and classification models are built with high accuracy and performance [45]. In the implementation considered in this work, we considered an exponential kernel k xi, xj = σ2 f exp (−r/σl) (3) being xi, xj ∈ Rn, σf is the signal standard deviation, and σl is the characteristic length scale. Finally, r is defined as the Euclidean distance between the vectors xi and xj r = xi − xj T xi − xj After the validation phase, the kernel parameters for the best case were set to σf = 4.6873 and σl = 0.7051. 4) Neural Network: The last of the considered classical algorithms was a fully connected feed forward NN. This is one of the most classic ML algorithms, already referenced in the middle of the last century, and a pillar of the most complex networks used nowadays in deep learning [46]. In this work, we implemented a simple configuration with a single hidden layer consisting of 100 neurons with a rectified linear unit (ReLU) activation function, and a linear activation function in the output layer. All these parameters, as in the rest of the algorithms, were obtained using the Bayesian optimization mechanism limited to 50 iterations.

4.1 Fine Time Measurement

The ESP32-S2 [37] is an evolution of the famous ESP8266, massively used in automation projects, which introduces new Bluetooth and Wi-Fi capabilities. Both ESP32-S2 and ESP8266 SOCs are part of a family of low-cost SOC micro controllers from Espress if Systems, a Chinese company from Shanghai.

In particular, the ESP32-S2 and the ESP32-C3 series have recently added support for the IEEE 802.11-2016 standard, which introduces the FTM protocol to provide ranging estimates using Wi-Fi links. Basically, this protocol measures the RTT between two devices and, based on this time, estimates the distance between them. These devices can be of any type (access points (APs), mobile terminals, SOCs, etc.), provided that they have a Wi-Fi chipset compatible with the 802.11-2016 standard and a firmware that supports FTM. Due to its enormous market penetration, this work focuses on the ESP32-S2, although the results should be similar for the frequency band. The results showed an accuracy about 1 m in open space (after correction for a constant offset), and about 5 m in indoors. This work also showed little difference between using 20 or 40 MHz bandwidths at the 2.4-GHz band. However, there was a clear improvement when using the 80-MHz bandwidth in the 5-GHz band.

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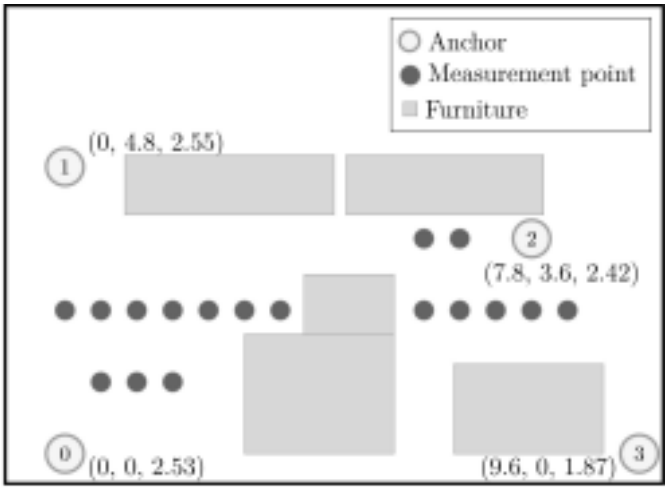


Figure 2: *Measurement setup of the scenario in the Scientific Area building. Anchors 0 and 1 use a bandwidth of 20 MHz, whereas anchors 2 and 3 employ 40 MHz.*

5 Future Work

In this work, we have analyzed the performance of the ESP32-S2 module as a device capable of providing distance estimation using FTM Wi-Fi technology implemented according to the IEEE 802.11-2016 standard. For this purpose, we have performed several measurement campaigns in different scenarios, using several ESP32-S2 devices with a specific firmware. Subsequently, we have evaluated the estimates obtained, resulting in high error values in indoor environments (up to 5 m for the 75% of the measurements with a bandwidth of 20 MHz) and lower errors in outdoor environments (up to around 1.5 m for the 75% of the measurements with a bandwidth of 40 MHz and up to 2.5 m when the bandwidth is 20 MHz). This difference in the error levels is due to several factors. One of them is the utilization of an algorithm based on an energy threshold to perform the temporal marking of the packets during the FTM protocol. In this case, multipath and interference problems in indoor environments cause that the first path of the signal be missed, and a bounce is taken instead. In this case, the time of flight (TOF) of the signal becomes longer than the actual one, and therefore the distance estimation is also longer.

6 Conclusion

We have proposed to use classical ML algorithms to perform the final distance estimation, taking as training features the raw RTT values and the signal level indicator of each sample. We have trained and tested the algorithms, showing an improvement in the absolute error obtained. Additionally, we have implemented one of these trained algorithms inside the ESP32-S2, so that we have been able to generate the estimates in real time and simultaneously with those provided by the chip. An additional measurement campaign was carried out, in a totally different scenario from those considered to obtain the training

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samples, with the objective of validating the ML algorithms and the real-time implementation. The results obtained, despite the difficulties of the environment, demonstrated that our proposal based on ML is suitable to address the problem of generating the final estimates from the RTT values. Overall, the FTM implementation in the ESP32-S2 is still far from being usable in complex indoor environments. While its performance in outdoor environments exhibited good results, with almost 90% of the samples below 2 m of absolute error for a bandwidth value of 40 MHz, in indoor environments, only 40% of the samples fall below such a threshold (for a bandwidth value of 20 MHz).