Towards Improved Indoor Location with Unmodified RFID Systems

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Abstract: The management of health systems has been one of the main challenges in several European countries, especially where the aging population is increasing. This led to the adoption of smarter technologies as a means to automate the processes within hospitals. One of the technologies adopted is active location solutions, which allows the staff within the hospital to quickly find any sort of entity, from key persons to equipment. In this work, we focus on developing a reliable method for active location based on RSSI antennas, passive tags, and ML models. Since the tags are passive, the usage of RSSI is discouraged, since it does not vary sufficiently based on our experiments. We explored the usage of alternative features, such as the number of activations per tag within a time slot. Throughout our evaluation, we were able to reach an average error of 0.275 m which is similar to existing RSSI IPS.

1 INTRODUCTION

The management of health systems and their economic viability, especially in western countries where the aging population is increasingly significant, and has been one of the main challenges for several European countries. With an increase in the number of patients and difficulty in making annual budgets keep up with this growth. Hospitals, as well as other clinical centers have been looking for new solutions that enable them to maximize service efficiency, reduce costs and increase patient satisfaction. To automate these processes some hospitals have started to adopt active localization technologies through Radio Frequency Identification (RFID) (Paiva et al., 2018; Tegou et al., 2018). Using Random Forest (RF) technologies, it is possible to monitor the movement of patients through the various hospital sectors, as well as the location and use of medical equipment, and even the stock and supply of medications to patients.

This paper aims to explore solutions based on RF, for indoor localization of resources. The developed models have, as requirements, the speed of response, the accuracy of the location and the lowest volume of data for each prediction (minimizing the electrical consumption by parts of the RFID radios). The work described is part of a research project aiming for a low-cost indoor location system using commonly acquired RFID antennas and tags.

Ideally one would use RFID based technology for developing an Indoor Positioning System (IPS). However, during our experiments RFID technology with passive tags did not produce enough information for developing an accurate IPS. The main outcome of this work is the exploration of alternative features, that can be used to develop IPS with accuracy levels similar to traditional ones based on RFID.

The remaining document is organized as follows. section 2 described the current state of the art for active indoor location. The following section (section 3) describes the hardware used in the execution of this study. section 4 presents the proposed solution. We describe the results of our evaluation on section 5. Finally, the conclusion can be found on section 6.

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2 STATE OF THE ART

In the past two decades, IPS have been increasing in popularity, due to the wide range of technologies and value they can provide to multiple business areas.

There are multiple techniques used in location systems, such as multilateration (Carotenuto et al., 2019), angulation (Pomárico-Franquiz et al., 2014), fingerprinting (Suroso et al., 2021) and others. These techniques require some information provided by the antennas and tags used, like the Time of Arrival (ToA) (Shen et al., 2014), Angle of Arrival (AoA) (Xiong and Jamieson, 2013) and Received Signal Strength Indication (RSSI) (Hightower et al., 2001). The tags used in these systems can be active or passive.

SpotON (Hightower et al., 2001) is a location system that uses RSSI to locate active RFID tags in a three-dimensional space. LANDMARC (Ni et al., 2003) is a system that also reflects the relationship between RSSI and power levels and makes use of reference tags and the K-NN algorithm to estimate the positions. It has an accuracy of 2 m and a location delay of 7.5 s. In (Suroso et al., 2021) Dwi *et al.* propose a fingerprinting based positioning system using a RF algorithm and RSSI data, which achieved an error of 0.5 m, which is 18% lower than the compared Euclidean distance method. In (Chanama and Wongwirat, 2018), Lummanee et al. compare the performance of a Gradient Boosting algorithm to a typical Decision Tree (DT) applied in a positioning system. The experiment was based on a 324 m^2 area divided in 9 zones. The DT based Gradient Boosting algorithm achieved an estimation error of 0.754 m for 19 reference radio signals at 50 samples per zone, 17.8% more accurate than the typical DT. In (Choi et al., 2009) Jae *et al.* developed a passive RFID based localization system which uses RSSI information and reference tags to predict one-dimensional position of the asset. It achieves an error of 0.2089 m using the K-NN technique in a 3 m space.

These methods are mainly based on RSSI, which has the disadvantage of suffering greatly from attenuation due to internal obstacles and dynamic environments. Unlike SpotON and LANDMARC, the approach in (Wilson et al., 2007) by Wilson *et al.* does not depend on RSSI, however, is based on the same RSSI principles. This research work is based on passive RSSI technology. Two scenarios of stationary and mobile RSSI tags are considered. The method gives tag count percentages for various signal attenuation conditions. The tags are located by recording characteristic curves of readings under different attenuation values at multiple locations in an environment. Similarly, Vorst et al. (Vorst et al., 2008) use passive RFID tags and an onboard reader to locate mobile objects. Particle Filter (PF) technique is exploited to estimate the location from a prior learned probabilistic model, achieving a precision of 0.20–0.26 m.

3 HARDWARE DESCRIPTION

Given the setting where this work has developed, the hardware was pre-selected. The hardware consists of two units (processing + radio), that communicate with each other through a physical bus (RS232, RS485 or Ethernet). The local processing unit was designed to have Long Term Evolution (LTE) and Ethernet communications support, a 230 V Alternating Current (AC) power supply and an Advanced RISC Machine (ARM) processor running a GNU/Linux operating system with low power consumption. The antenna model is quite common and is used as provided by the manufacturer without any custom firmware. The use of unmodified hardware increases the usability and availability of the system while reducing its price. The drawback is that the antenna processing capabilities or the information that it reports may be sub-optimal. According to the manufacturer there is an automatic gain compensation done at the firmware level. This is done to allows the detection of the passive tags. The work we present aims at bringing value by providing an effective solution, even with unmodified hardware.

Figure 1 presents the smart antenna module used as well as RFID tags.

The communication between the antenna and the tags is made through a carrier wave in the 865–868 MHz (Ultra High Frequency (UHF)) frequency range as defined in the EN 302 208 v3.2.0 [1] directive for the European region, and cannot exceed 2 W emission power. In this way, the antenna controller allows the RF emission power adjustment 0–300 mW, allowing readings up to 25 m and writings up to 6 m according to the manufacturer. The antenna polarization is circular with a gain of 12 dBi. The controller uses the Impinj R2000 chipset supporting the EPC C1 GEN2 protocol [2], ISO18000-6C [3] (see Table 1). This setup should be one of the most commonly used, as the hardware and chipset are very popular. We see this as a major contribution from our work, as the output can be applied to a wide set of existing or future,

[1] https://www.etsi.org/deliver/etsi_en/302200_302299/302208/03.02.00_20/en_302208v030200a.pdf

[2] https://www.gs1.org/standards/rfid/uhf-air-interface-protocol

[3] https://www.iso.org/standard/59644.html

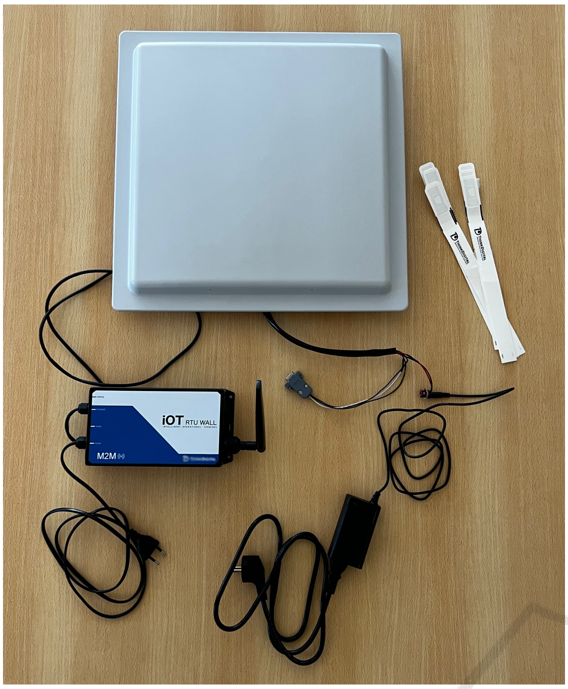


Figure 1: Smart Antenna and passive RFID tags used for data gathering.

Table 1: Specification of the RFID UHF reader and writer.

Product Parameter	Parameter Description
Model	ACM818A UHF (20M)
Tag Protocol	EPC C1 GEN2 / ISO 18000-6C
Output Power	Step interval 1.0dB, maximum +30dBm
RF Power Output	0.1W - 1W
Built- in Antenna Type	12dbi linear polarization antenna
Communication Ports	1)RS-232 2)RS-485 3)Wiegand 26 \ 32 bits
Communication Rates	115200bps
Reading/Writing	20m
Multi-tags Reading	200tags/s
Working Voltage	DC +12V

deployments.

The real-time communication with the smart antenna is achieved using an MQTT broker, over which we implemented several control functions: a) Definition of emission power of the antenna; b) Tag reading request over a time window (burst); c) Return data obtained at the end of the reading; d) Direct interaction with an antenna to manage it.

4 PROPOSED SOLUTION

The goal of the Machine Learning (ML) models proposed in this work is to estimate the distance between the passive tag and the antenna, based on the different features collected. This problem can be modelled as a traditional regression model, the following models were selected since they represent well-established and widely used models in the community: i) K-Nearest Neighbors ii) Decision Tree iii) Random Forest iv) Support Vector Regressor v) Gradient Boosting Regressor

The solution was implemented using the Scikit-learn[4] library, which is a very popular and robust tool for RF and statistical modelling in Python. It is important to mention that we used the default hyperparameters of each method unless stated in the following subsections.

The first step consists of the analysis and preparation of the data gathered from the antenna. The initial solution was developed using single RSSI values as the input. The features were normalized using the MinMaxScaler normalization technique. After the normalization step, the multiple regression algorithms were trained and evaluated. The output is the distance (in meters) between the antenna and the RFID tag. The architecture of the solution is described by Figure 2.

It is important to mention that the following experiments were conducted in an isolated environment to ensure the validity of the results. The following subsections present the multiple experiments conducted in the pursuit of a viable IPS, which is achieved by determining and characterizing the most adequate features present in the RFID system.

4.1 Experiment 1

The first experimental procedure involved data capture, using a passive RFID tag placed at several distances from the RF antenna, obtaining the RSSI values. Readings were performed from 0.5 m to 5 m, with 0.5 m increments (distance between the RF antenna and the RFID tag), using different values of emission power, from 100 mW to 300 mW, during a predefined time interval of 60 seconds (see Figure 3).

From the result of this first experimental procedure, it can be observed that the measured RSSI values are not proportional to the known distance values for each reading interval. This happens because the RF antenna, by default, performs an automatic compensation of the emission power gains, which translates into constant average values, unrelated to

[4]https://scikit-learn.org/

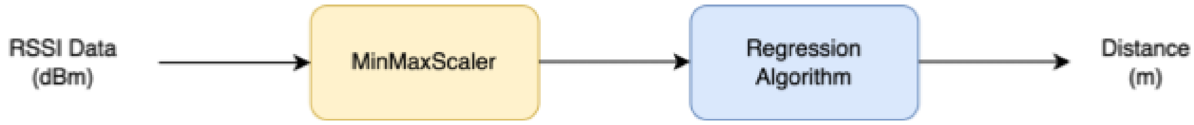


Figure 2: Architecture of the first ML solution based on RSSI data.

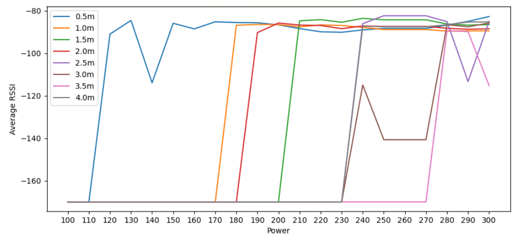


Figure 3: Average RSSI values from different power levels and distances.

the known distance values for the passive RFID tags arranged on site. This strongly diverges from the vendor-provided information and should be considered with great care by other researchers. It also makes it unfeasible to apply ML models over the RSSI values provided by the hardware.

Due to the fact described above, it was decided to proceed with the hardware characterization study, seeking to obtain new feature sets that vary in a meaningful way with the distance. This will be important for other researchers, as the features can be replicated over other types of hardware.

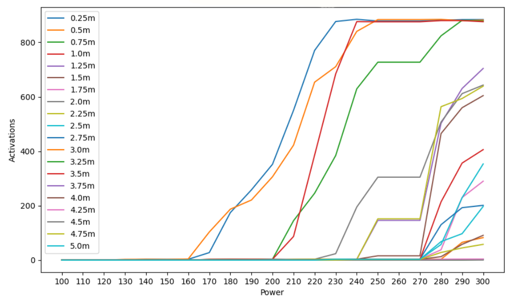
4.2 Experiment 2

The second experimental procedure was performed in the same way as the first one, that is, through emission power scans, between 100 mW and 300 mW. However, in this case, during shorter pre-defined time intervals (20 seconds), for distance values from 0.25 m to 5 m, with increments of 0.25 m (distance between the RF antenna and the RFID tag). The following hypothesis was formulated:

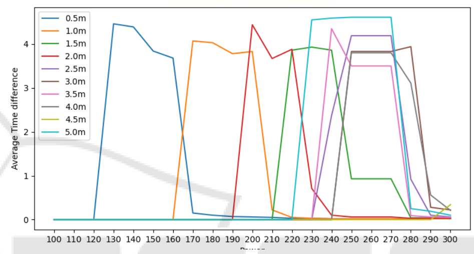
Hypothesis 1. *For the same emission power value, the number of activations registered by the antenna decreases as the distance increases.*

From this second procedure the following results were obtained (see Figure 4):

By observing Figure 4a, there is a clear increase in the number of activations as the emission power increases. It can also be seen that the number of activations decreases as the distance increases, for each power value, validating Hypothesis 1. It can be noticed that the relations are not constant, since the tag presents a higher number of activations at a distance of 1 m than at 0.75 m between the powers 220 mW



(a) Number of activations in function of power and distance.



(b) Average time delta between activations in function of power and distance.

Figure 4: The results for the second experiment.

and 280 mW. This behaviour could be explained by possible external factors. It can be noted that similarly to the previous experiment, the number of activations was purposely kept constant when the power is equal to 260 mW and 270 mW since the antenna did not register activations at these powers.

Figure 4b represents the average time between activations (in seconds) for each power and distance considered. Time peaks between activations can be verified for each distance as the power increases. Since, for a given distance, there are no activations up to a given power (160 mW for distance 1.0 m), the average time between activations has been forcefully set to 0. After activations occur at the first few power levels, this time rises substantially, reaching a peak. As the emission power increases, there is a decrease in the average time between activations. It is thus verified that these peaks occur at higher powers as the distance increases.

After verifying the experimental results, a second ML solution was developed to predict the tag distance from the antenna, according to the number of activations and the average time between activations, per scan. However, in this experiment, 10 iterations were performed for each power and distance value. This way, there is more data available for algorithm development, the first 7 iterations for training and the last 3 for testing. A dataset was generated containing 200 readings, 140 for training and 60 for testing. Figure 5 represents the second solution architecture.

Given the available number of power levels, we applied feature reduction technique, namely SelectKBest [5] with the score function `mutual_info_regression`. The 200, 280, 290 and 300 power levels are the ones that result in the lowest error. Table 2 contains the results of the accuracy of the models for the power levels considered. The first three columns represent the error of the models trained with all the emission power values and the last two columns represent just the models trained with the selected power values. The algorithm that obtained the lowest error (0.00 m) was K-Nearest Neighbors (K-NN) with k=1. This model obtained the same optimal performance for all feature groups, except when these were only the average number between activations, where the error was the highest compared to the other algorithms (0.80 m).

The RF algorithm had, in general, a good performance, obtaining in almost all cases the second smallest error besides K-NN, something that was also verified in the previous experiment. The Support Vector Regressor (SVR) proved to be the algorithm with the worst performance, presenting errors constantly above 0.58 m for the various groups of features.

It can be seen that models trained only with the mean time between activations obtained the worst performance, followed by models trained with both the number of activations and the mean time between activations.

The models trained with emission powers of 200, 280, 290 and 300 mW obtained a lower error than the remaining algorithms trained with all powers, especially when the features are only the number of activations. Thus, it can be concluded that the feature reduction technique applied had a positive impact on the algorithms' performance.

Table 2: RMSE (in meters) for the prediction of the distance between the tag and the antenna for each group of features.

RMSE (meters)	Activ.	Time	All	Activ. (4 pwr)	All (4 pwr)
K-NN	0.00	0.80	0.00	0.00	0.00
SVR	0.58	0.69	0.58	0.58	0.59
GBR	0.31	0.63	0.38	0.13	0.24
RF	0.22	0.64	0.29	0.15	0.21
DT	0.24	0.66	0.66	0.18	0.26

[5]https://scikit-learn.org/stable/modules/generated/sklearn.feature_selection.SelectKBest.html

4.3 Experiment 3

The third experimental procedure was performed in a larger space, using one dynamic RFID tag and 9 static RFID tags (as references), placed from 1.0 m to 9 m from the RF antenna (spaced 1 m each). The emission powers considered in this procedure were only those that obtained better readings in the previous procedures, which were 280, 290 and 300 mW, for distance values from 0.5 m to 10 m, with 0.5 m increments (distance between the RF antenna and the RFID tag). From this procedure the following graphs were obtained (see Figure 6):

Figure 6a shows a decrease in the number of activations over time. It is also noted that the lower power (280 mW) obtains a higher number of activations from 1 m to 2 m, which is unexpected but verified in the previous experiments.

The number of activations falls sharply until a distance equal to 4 m, remaining low but not equal to 0 until 5 m and recording a peak at 6 m where the activations reach 30 for the 300 mW power. Afterwards, this number remained quite low until 9 m and null for any power at 10 m.

Figure 6b depicts the average time between activations. In the first distances, the smaller emission power (280 mW) shows a shorter time between activations, and this time increases with the increase of the distance. Although there are no activations for the powers 280 mW and 290 mW starting at 6 m, the preprocessing applied to the time between activations makes this number remain high, thus maintaining the relationship with the distance.

The graphs presented in Figure 7 show the difference between the number of activations between the dynamic tag and the 9 static tags, for each emission power. It can be seen that, in all graphs, the difference decreases with distance, as would be expected. There is a clear relationship between the position of the static tags and the difference between activations, as this difference is smaller the closer the static tag is to the antenna.

In Figure 7a, it can be seen that these remain practically constant from 4 m on since at this power of emission there were practically no activations of the dynamic tag.

5 EVALUATION

Based on the results from the previous experiments we formulated a second Hypothesis 2:

Hypothesis 2. *The difference in the number of activations between the dynamic tag and the reference tags*

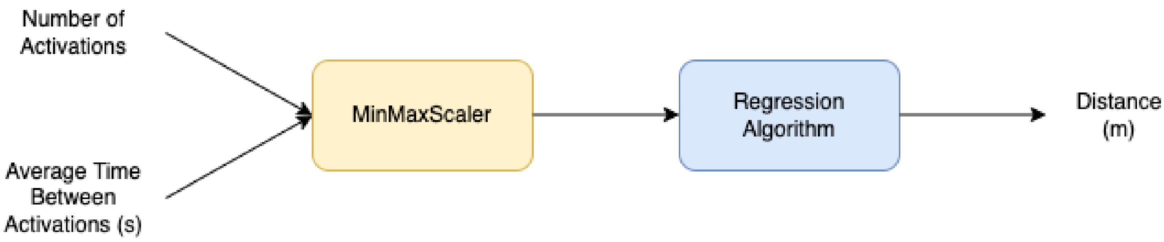
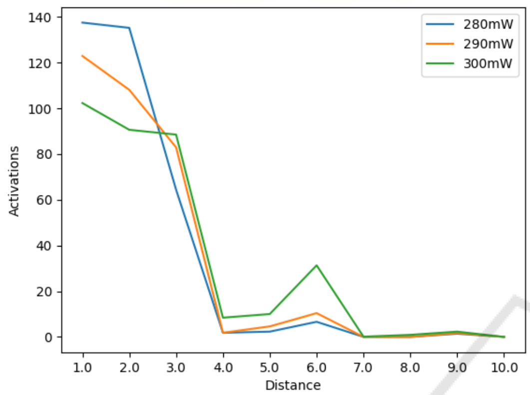
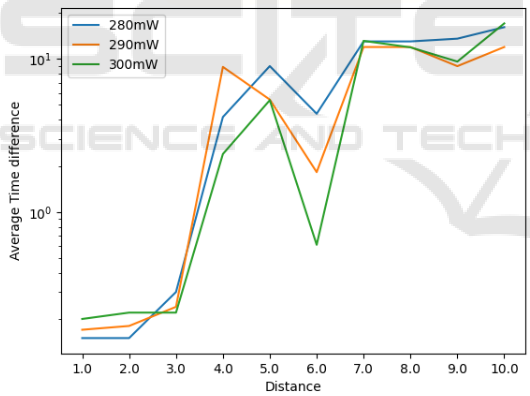


Figure 5: Architecture of the second ML solution based on the number of activations and the average time between activations.



(a) The number of activations for different power levels and distances.



(b) Average time delta between activations as a function of power and distance.

Figure 6: The results for the third experiment.

contributes to a performance increase.

A third RF solution was developed using the same algorithms used in the previous experiments but also using the difference between the number of activations. The developed models were trained and tested using the generated dataset containing 200 readings. The architecture is described in Figure 8.

The results were recorded in Table 3. The errors obtained in the tests showed that the models that were trained with groups of features that included information regarding the difference between the number of activations obtained better performance than those that did not include this information, validating Hypothesis 2.

Table 3: RMSE (in meters) for the prediction of the distance between a tag and the antenna, for each group of features.

RMSE (meters)	Activ.	Time between activations	Difference between activations	All
K-NN	1.19	1.21	0.72	0.72
SVR	1.45	1.26	1.33	1.32
GBR	1.25	0.76	0.84	0.72
RF	1.19	0.85	0.75	0.57
DT	1.48	1.03	1.67	1.08

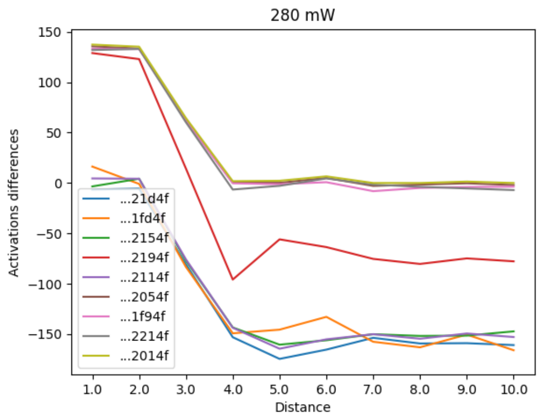
Several models trained only with the differences between the number of activations between the dynamic tag and the reference tags for each of the three emission power levels were elaborated. The number of reference tags and the tags themselves used to train the algorithms was varied, identifying which combinations result in the lowest error for the various numbers considered. The errors for each model tested are shown in Table 4.

Table 4: RMSE (in meters) for the prediction of the distance between one tag A and the antenna in experiment 3, using a set of different reference tags.

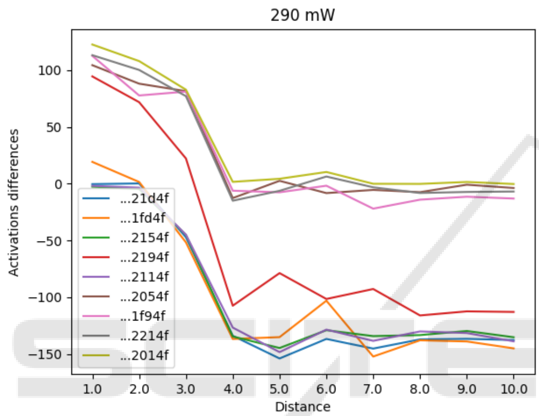
RMSE (meters)	2 tags	3 tags	4 tags	5 tags	All
K-NN	0.67	0.60	0.55	0.60	0.72
SVR	1.27	1.37	1.29	1.27	1.33
GBR	0.77	0.76	0.69	0.78	0.84
RF	0.72	0.75	0.72	0.79	0.75
DT	1.08	1.11	1.14	1.74	1.67

Overall, the models that used all the available features obtained the best performance, followed by those that used only the difference between the number of activations. The models trained with only the average time between activations obtained a performance similar to those that used the difference between the number of activations, and the models trained only with the number of activations obtained the worst performance.

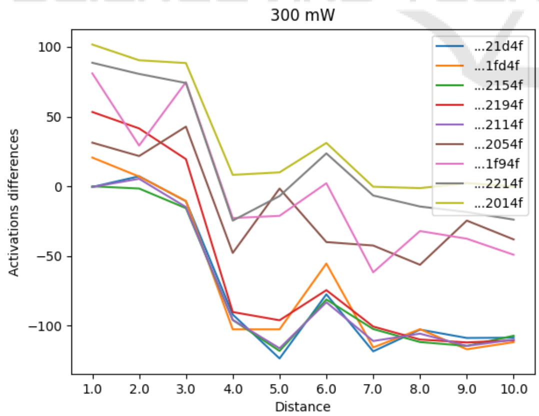
Comparing the different algorithms applied, it can be seen that SVR obtained the worst performance,



(a) 280 mW.



(b) 290 mW.



(c) 300 mW.

Figure 7: The difference of activations recorded for the dynamic RFID tag and the reference tags, by reading interval (20 seconds), for the 280, 290 and 300 mW powers considered, at different distances, with 0.5 m increments. The colours shown in the graph correspond to reference tags placed from 1.0 to 9.0 metres, respectively.

with an error greater than 1.25 m in all tests. The DT algorithm also did not obtain a good performance, since the error was always higher than 1 m. The lowest error was obtained by the RF algorithm (0.57 m) which obtained a good performance in several tests.

Through Table 4 it is possible to verify that the smallest error was 0.55 m, obtained by the K-NN algorithm with k=3, using 4 reference tags at 3, 6, 7 and 9 meters away from the antenna. The Gradient Boosting Regressor (GBR) and RF algorithms also obtained the best performance using this group of features.

From the results obtained in this experiment, it can be concluded that the use of static reference tags contributes positively to the development of more accurate models.

6 CONCLUSION

The management of health systems has been one of the main challenges in several European countries, especially where the ageing population is increasing. One of the technologies adopted is active location solutions, which allows the staff within the hospital to quickly find any sort of entity, from key persons to equipment.

In this work, we evaluated the usage of dedicated hardware (namely the RF antenna) for indoor location within a medical environment. Our initial test showed that RSSI was unreliable as a feature for our specific hardware. This happens because the RF antenna, by default, performs an automatic compensation of the emission power gains, which translates into RSSI value that does not change with the distance (for the passive RFID tags arranged on site).

The main contribution of this work is the usage of alternative features to overcome this issue and achieve reasonable accuracy with vanilla hardware. The final model uses the number of activation and the average time between activations from a selected range of power levels as the features for indoor location.

Comparing the results obtained with the systems studied in section 2, it is possible to conclude that the accuracy of the developed models is on par without using RSSI data. It obtained an error of 0.00 m within a range of 5 m in the second experiment and an error of 0.55 m within a range of 10 m in the third experiment, resulting in an average error of 0.275 m. The approach in (Choi et al., 2009) achieves an error of 0.2089 m but within a shorter space of 3 m using RSSI data.

These results only serve to present an alternative set of features for specific hardware, whenever the typical RSSI metric can not be easily applied. The

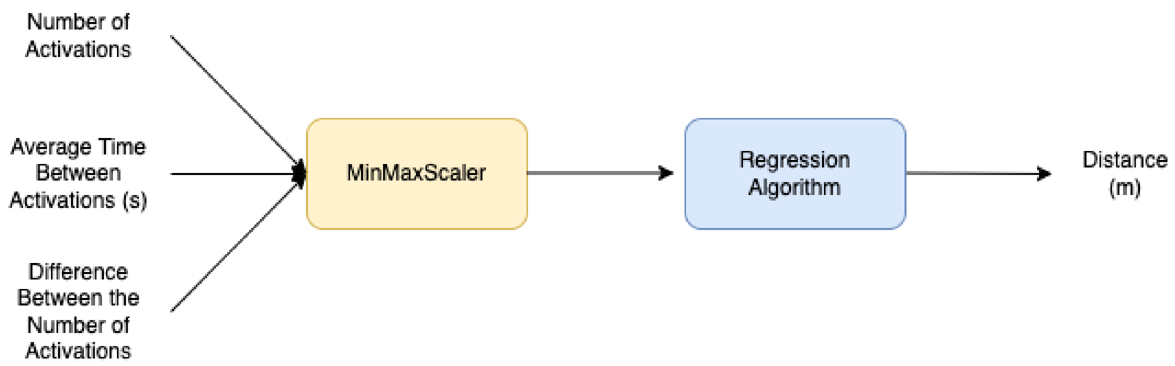


Figure 8: Architecture of the third ML solution based on the number of activations, the average time between activations and the difference between the number of activations.

proposed features present an adequate level of performance. Regardless further testing is required since the proposed feature can be highly correlated with the specific hardware, limiting the deployment of generic location models.

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