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PROIECT DE DISERTAȚIE

Localizare în interiorul clădirilor folosind puterea semnalelor WiFi și senzorii inerțiali ai telefoanelor mobile

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MASTER THESIS

Indoor localization using WiFi signal strength and inertial sensors on smartphones

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BUCHAREST

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# Sinopsis

Localizarea interioară a devenit un subiect foarte important în ziua de astăzi, datorită aplicațiilor în diverse domenii și scenarii, cum ar fi crearea rutelor în interiorul clădirilor de birouri, ghidarea rapidă a echipelor de intervenții și mobilizarea roboților mobili ajutători din cadrul fabricilor. Din păcate, în momentul actual nu există o metodă general valabilă pentru implementarea unui sistem robust de localizare interioară, cu costuri minime și estimări cu acuratețe ridicată, fiecare metodă de implementare și tehnologie utilizată având atât avantajele, cât și dezavantajele sale. În cadrul acestei lucrări vor fi prezentate tehnologiile utilizate în cadrul soluțiilor deja existente, în special cele folosite în cadrul sistemele bazate pe utilizarea telefoanelor mobile, dar și metodele de implementare ale acestora. Pornind de la tehnologiile existente, în cadrul acestui proiect se va prezenta realizarea unui algoritm de localizare interioară bazat pe învățare automată cu rețele neurale adânci care va folosi puterea semnalului wireless în diferite zone ale clădirii, dar și o metodă ce va folosi rețele neurale recurente și va avea ca date de intrare valorile continue ale senzorilor inerțiali cu care un telefon mobil este dotat din fabrică.

# Abstract

Indoor localization has become a very important topic in this day and age, thanks to applications in various fields and scenarios, such as creating routes inside office buildings, quickly guiding intervention teams and mobilizing mobile helper robots in factories. Unfortunately, at the moment there is no generally valid method for implementing a robust indoor location system with minimal cost and high accuracy estimates, each implementation method and technology used having both its advantages and disadvantages. In this paper, the technologies used in existing solutions will be presented, especially those used in smartphone-based systems, and also their implementation methods. Starting from the existing technologies, this project will present the realization of an indoor localization algorithm based on machine learning with deep neural networks that will use the wireless signal strength in different areas of the building, but also a method that will use recurrent neural networks which will have as input data the continuous values of the inertial sensors with which a mobile phone is equipped by default.

# INTRODUCTION

Indoor localization represents the capability of detecting objects or people inside covered buildings, places where in most cases the GPS signal is weak or non-existent [1], it being limited to outdoor areas where the signal strength of the satellites is stronger, thus having good enough coverage only in open spaces. This is why people had to come with new ideas of detecting objects without the need of GPS, so additional technologies have started to emerge.

## Context

Indoor localization is achieved using multiple indoor positioning systems (IPS), those being passive or active, consisting of networks of interconnected sensors and devices that generate data that can be used to estimate the position of an item in the real world relative to predetermined fixed points.

Some of the main areas where this type of navigation could improve our lives are:

* Smart workplaces – using this technology, the employees could find each other with ease or could find key points in the building (meeting rooms, utilities, their colleague’s location), in this way enhancing the company’s productivity and security. Also, the companies could create floor heatmaps of the most popular places to improve the quality of the work environment (additional disinfection, improving or remodeling the areas with poor traffic);
* Airports – using indoor localization, travelers could easily find points of interest that might otherwise be harder to find (luggage lanes, available check-in points, shops, restaurants, bathrooms) and they could also be guided effectively to their designated gateway, thus avoiding mistakes, and lowering the probability of missed flights caused by the plane departing from other lanes than the initial ones;
* Retail stores – with the help of indoor localization, customers could easily find the target stores that they want to reach, and they can also access a personalized route depending on their shopping preferences/habits. Stores could also introduce personalized ads based on the users once they are approaching them or are nearby. In addition, in the case of malls, they could also implement customized strategies based on the flow of people and the areas most visited by them, thus being able to optimize the resources allocated to increase profits;
* Assistance systems for people with disabilities – through an indoor navigation system, people with special needs could have it much easier to find different areas or products, without the need of a special person to guide them, it would also lower the effort needed to establish the surrounding environment;
* Universities – with the help of indoor localization systems, it would be much easier to students who are not yet familiar with the university’s layout to find their classrooms and laboratories, being especially helpful for persons who must be in different places within short timeframes. It could also help visitors to find the important attractions in case of events like tech fairs or job finding events organized by companies;
* Other locations and events with many people, where finding others is difficult due to the lack of an exact position in space (festivals, concerts, sport events).

Taking into consideration the tremendous advancements of the smartphone devices, with their integrated sensors and processing power, but also their high availability to a majority of the population, many new technologies and algorithms have emerged in order to resolve the issue at hand and its multitude of possibilities, making mobile devices the perfect tool for indoor positioning applications.

## Problem

Due to the inability to provide an accurate position inside buildings with the help of global positioning systems, it is necessary to use other types of technologies that can be implemented for indoor localization, such as radio frequencies, light waves, acoustic waves, images, or internal mechanical systems (Figura 1) [2].

Diagram

Description automatically generated

Figure 1. Categorization of the technologies used for idoor positioning, image taken from [2]

Each of the technologies shown in Figure 1 has it’s own unique characteristics, capabilities and restrictions, their usage being highly influenced by several factors, such as the element to be located, the device that verifies the location, the size of the area checked, etc. Considering all those factors, many devices and services are developed in order to make location based applications perform as highly accurate as possible, ranging from mobile helper robots in factories to product searching applications inside retail stores.

While this is a highly researched domain and great efforts have been made to increase the precision of the indoor positioning, especially for smartphone-based applications, there are still not enough large-scale high accuracy localization algorithms that could be easily implemented in different types of locations and dynamic environments without extensive data mapping or adding new infrastructure.

## Objectives

This paper aims to present the research of a smartphone-based deep learning interior localization algorithm that uses the data from its integrated inertial and Wi-Fi sensors. We will analyze the effectiveness and performances of deep learning algorithms for the issue at hand, will compare and evaluate the accuracy and the reliability of the used algorithms in the context of indoor positioning, will enhance the presented models in order to achieve a higher result accuracy and will highlight their advantages and potential improvements.

With this objective in mind, we will present the used data and its processing, but also the algorithms used to estimate the user’s position, their implementation and the final results.

By doing this, we hope to further advance the research for a future highly-accurate, reliable and easy to implement smartphone-based indoor localization method that could help humans eliminate the constraints of indoor positioning systems.

## Structure

This paper is organized as follows. In Chapter 2 we will present the State of the art for the indoor localization field

TODO

# RELATED WORK

Navigation systems are technologies that help users to get to the desired point in unknown areas without prior knowledge of the specific place. Due to the fact that the GPS can’t provide reliable results in the case of indoor positioning by not having direct line of sight with the satellites, it is necessary to use other methods of localization inside buildings.

## Technologies used for interior positioning systems

Among the main types of technologies that are currently used for indoor localization with the help of smartphones, we have [2] [3] [4] [5]:

1. **IMU (Inertial Measurement Unit)** – is uses integrated sensors such as the accelerometer, gyroscope or magnetometer to detect the direction, distance and speed at which the device is moving through space. One of the bigges disadvantages of this technology is the rapid accumulation of errors in the classic aproaches, where even the smallest deviation can lead to gross errors in estimating the user’s location. In order to minimise these problems, we must apply complex algorithms so that every movement of the user and the phone are detected correctly;
2. **RFID (Radio Frequency Identification)** – represent smart tags containing an integrated circuit and antenna that can be detected by a reader via an electromagnetic field. They can be passive (needing to be turned on by a reader before they can be scanned), or active (they have a built-in battery and can transmit a signal continuously throughout their operating time).

In the case of passive labels, RFIDs can be positioned on the ground’s surface as to form matrices that, after detection, can estimate the location of the reader [6] [7] [8];

1. **BLE (Bluetooth Low Energy)** – this technology doesn’t require a big quantity of energy to work, having also a relatively low cost, it is created for data transfers at short distances and low data loads [9]. For this type of identification, several transmiters have to be mounted in the building, the user’s location being calculated by measuring the distance between the smartphone and the three nearest signal transmiters. BLE devices operate on a 2.4 GHz frequency and have their own battery and can be placed on any surface of the location where the localization is desired to be made (being in opposition to the Wi-Fi acces points that have to be located near a power source). In addition, most of them have an open source protocol, being compatible with the operating systems of all existing mobile companies [3];
2. **Wi-Fi** – this technology is based on Wide Local Area Networks (WLAN) and is based on the IEEE 802.11 standard, operating on frequencies betweehn 2.4 GHz and 5 GHz. The position of the target device is calculated by determining either the distance or angle between it and the nearest acces points or by the strength of the signal, these values being then included in different algorithms for a more accurate location. Due to the fact that the Wi-Fi acces points are not mainly used for localization, but for the transmission of information, it is necessary to use complex algorithms for interpreting the data obtained from them.

In terms of information usage, Android systems provide developers with their own API for capturing information related to the signal and access points, but it has some disadvantages caused by security reasons introduced starting with Android 8.0., such as limiting the frequency of Wi-Fi scans allowed. For Apple devices, wireless signal verification is more difficult, as there is currently no API for iOS systems.

1. **UWB (Ultra-Wideband)** – it is an alternative technology ti Wi-Fi and Bluetooth, it works at very high frequencies, the detection being made by calculating the distance between the transmitter and the receiver located in the smartphone (or any other device that we want to localize). This system is very efficient in terms of energy consumption, but it has the disadvantage of a short detection distance [2]. The positioning systems that use UWB are quite precise, they can reach an accuracy between 0.1 and 0.2m [10], but the devices are still quite expensive and for localization there is the need of installing the extra hardware infrastructure.
2. **Cellular networks** – uses long-range wireless networks, which are distributed over cells consisting of several antennas. Among the advantages of using this technology are the existing infrastructure, the very high coverage, the availability of different frequencies and the applicability on different types of mobile phones. With the use of the new generations of 5G technologies, the accuracy of indoor location can evolve considerably compared to previous generations due to high bandwidth and increased information transmission capabilities.

Currently, for the internal location of users via mobile phones, the most common detection methods are via Bluetooth, Wi-Fi, UWB and integrated IMU.

UWB technology is very promising in terms of accuracy, having the ability to penetrate materials such as cement, glass or wood, these being the main constituent elements of a building, but it is a relatively new technology, being integrated only in some of the the latest smartphone models (Samsung S21, Samsung S21 +, Galaxy Note 20 Ultra, iPhone 11/12), also having a fairly small coverage area (less than 100m).

Bluetooth technology is very good in terms of power consumption, the localization with this method is fairly widespread today, but its use involves relatively high additional costs, to use it is necessary to install transmitters 100m apart on the entire surface of the building.

Techniques and algorithms for calculating human actions can be used to estimate an user’s position through the IMU integrated in a smartphone, but the data obtained in this manner can lead tovery large errors by not having any external elements that can correct the estimation, the main focus of the recent research being the improvement of the localization based on past activites.

Locating smartphones via Wi-Fi is very promising, many researches being focused on developing new techniques and algorithms that can make the detection as accurate as possible in relation to the real user. Unlike Bluetooth and UWB technology, Wi-Fi hotspots are widespread, already existing in most large populated buildings (office buildings, malls, airports, hospitals), thus offering an economic advantage. A disadvantage of using this technology is the large number of factors that can disrupt the signal quality (walls, people, various materials), reducing the accuracy of detection.

Taking into account all the above mentioned factors, this paper’s research will be focused on researching, developing and enhancing state-of-the-art localization algorithms based on Wi-Fi signal strength and on the integrated inertial sensors of mobile devices.

## Positioning algorithms and principles for measuring distances using wireless signals and inertial sensors TODO: Verifica lucrarea aia [11] sa nu fie text prea similar la descrierile AOA, RTF, etc.

Due to problems such as multiple paths, lack of a direct signal path (lack of LOS) and other specific parameters of interior areas (presence of walls, objects, people, reflective or transparent areas), modeling radio propagation inside a building is quite of difficult [11]. To mitigate errors due to environmental disturbances, there are currently four types of algorithms used in internal positioning systems (Figure 2) [11] [2] [12] [13]:

- Proximity algorithms

- Triangulation and trilateration algorithms

- Algorithms for environmental analysis (Scene analysis)

- Dead Reckoning

Timeline

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Figure 2. Classification of methods to detect the indoor location on smartphones

**a) Proximity algorithms**

These algorithms are used not to detect the exact spatial position of a receiver, but to determine whether or not it is in a certain area. RFID tags, BLE or WLAN devices are generally used for this type of verification, the location being estimated to be the one with the highest RSS feed.

RSSI (Radio Strength Signal Indicator) – represents the verification of the power of a radio signal, this measure being represented in decibels-milliwatts (dBm), in the range [-120...0], the higher this number, the better the signal quality. As the distance between the transmitter and the receiver increases, the RSS degrades due to several factors such as: antenna transmission capacity, receiver quality, number of walls and floors encountered in the case of NLOS (Non-Line-Of-Sight) , the presence of people and objects [2].

The advantage of using this method is that it can be implemented on any type of smartphone and no prior synchronization of the transmitter and receiver is required.

**b)Triangulation**

Triangulation-based algorithms use information received from multiple access points to determine the position of objects. The measurement principle of this method is that of AOA.

AOA (Angle Of Arrival) – the location detection method that uses antennas that can determine the direction of propagation of a radio wave incident with the antenna array. AOA location systems estimate the position of a receiver as the intersection of imaginary lines located at the observed angle. A disadvantage of this method is the high price of hardware that can determine the transmission angle of the signal. At least two access points are required for this type of detection to generate the calculated angles.

**c)Trilateration**

Trilateration-based algorithms consider the estimated distances to the detected object, these being represented as imaginary lines that form triangles, then, through geometric formulas and through several intersections of these lines, estimates can be made of the actual position of a monitored object. The most important principles used in this method are RSS, TOA, TDOA, RSPM and RTT.

**TOA (Time Of Arrival)** – represents the time traveled by the signal from its transmission to the capture by the receiver, knowing in advance the transmission speed of the verified radio waves [11]. Using these distances, imaginary circles can be drawn around each access point, on the perimeter of which the searched element can be located. The exact position of the monitored object can be deduced by intersecting these circles from nearby access points.

**RSPM (Received Signal Phase Method)** – represents the calculation of the distance taking into account the time in which a phase delay to reach the transmitter. By using at least three access points, you can estimate the position on a 2D plane of the mobile phone that acts as a receiver [11].

**RTT (Round Trip Time) or RTOF (Returning Time OF Flight)** – is a relatively new method of determining the position that does not require synchronization of communication nodes. In this method, it is necessary to measure the time for a signal to go from a transmitter to a receiver and then return, it being introduced with Android 9 and being built on a new type of data packet called FTM (Fine Timing Measurement) [14]. The FTM protocol sends a request to a compatible access point, which sends back a request acceptance response and then the necessary information.

**d) Algorithms for environmental analysis**

These algorithms use a technique called fingerprinting, where signal strengths are measured in certain areas called reference points (RPs) and stored in a database along with their location and coordinates. In order to locate, the signal strength received by the receiver is measured, this being associated with the previously found reference points.

There are several methods of estimating location using fingerprinting:

- **Deterministic localization** - also called the method of the nearest neighbor (NN), in which the power of the signal received by the smartphone is measured, its location being associated with the reference point where the values are similar. For better values, more access points are used;

- **Probabilistic localization** - depending on the measured RSS, each reference point is assigned a distributed probability, the location being established as the one with the highest probability;

- **Localization with neural networks (deep learning)** - these take as input data the initial WiFi RSSI measurements and the access points locations, estimating the user's position according to different internal algorithms.

**e) Dead Reckoning**

These algorithms use the integrated inertial sensors of the smartphone to determine the user's movement and location, using various thresholds for different actions, such as walking, running, ascending stairs, or can detect the user’s movement patterns in order to estimate it’s location based on historic data. This type of algorithm is also used for map-matching, taking into account the real constraints to which people are subjected, such as the inability to pass through walls, movement in certain areas only through doors, etc. This information, correlated with the interior maps of the buildings, can provide useful information on the location of people (e.g. if a person goes to escalators, then waits for a number of seconds, it can be assumed that the person used that element to move), but it has a major disadvantage, that being the lack of an external verification that eliminates the gross errors caused by the noise of the sensors or erroneous estimates.

## Existing indoor localization algorithms

Even though there is currently no universal optimal method of indoor localization and no well-known standard, there are already various implementations of the algorithms and methods previously presented, many of them successfully combining them to achieve promising results. Among the most promising methods of location detection are those using WiFi signals and IMU integrated into mobile phones. Taking into consideration that for the majority of the methods of localization described in the previous chapter need information on the exact position in space or the specific parameters of the WiFi signal provided by the access points, a common goal for resolving the problem is finding ways of avoiding those shortcomings. As such, a big part of the latest research in the field is focused on using different machine learning techniques with hybrid single-modal or multimodal approaches that can use just the WiFi signal strength and inertial sensor data to predict the user’s position with as high accuracy as possible (see Table 1.).

Table 1 – WiFi and Inertial sensors based indoor localization solutions

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Reference | Estimation error  (m) | RSSI data | IMU data | Time series | Algorithms |
| [15] | 2.77 | Yes | No | Yes | CNN (Convolutional Neural Networks) |
| [16] | 1.35 | Yes | No | No | CNN, GPR (Gaussian Process Regression) |
| [17] | 1.3 | Yes | No | Yes | K-means clustering, KNN, SVM (Support Vector Machine) |
| [18] | 2.64 | Yes | No | No | Autoencoders, DNN |
| [19] | 1.67 | Yes | No | No | DNN (Deep Neural Networks), KNN (K-nearest neighbors) |
| [20] | 1.7 | No | Yes | Yes | OS-ELM (Online Sequential Extreme Learning Machine) |
| [21] | 2.6 | No | Yes | Yes | Mathematical calculations of the signal values, Kalman Filter |
| [22] | 1.8 | Yes | Yes | Yes | DNN, RNN (Recurrent Neural Networks), LSTM (Long-Short Term Memory) |

M. Ibrahim, M. Torki and M. ElNainay (2018) [15] have proposed a 3 step solution based on CNN (Convolutional Neural Networks) that takes as inputs a time series RSSI dataset of the recordings from different floors and rooms of an university building. The data is batched in period of times and then transposed in T x N arrays, where T is the number of consecutive recordings and N is the number of access points. By doing so, they are able to feed the processed data as inputs to the neural network, obtaining as results of the first step the building where the data has been recorded, in the second step the floor and in the third step the estimated position expressed as latitude and the longitude. Using this solution, they have been able to obtain 100% accuracy building prediction, 100% accuracy floor prediction and 2.77 m mean localization error.

Similar to this approach, G. Zhang, P. Wang, H. Chen and L. Zhang [16] have processed a Wi-Fi database containing fingerprints from the Jaume I University [23] in order to feed the data to a CNN algorithm, but further enhancing the algorithm by applying a Gaussian process regression (GPR) to the results of the position estimation, thus obtaining a mean error of 1.35 m between the real and predicted values.

Z. Chenbin, N. Qin, Y. Xue and L. Yang [17] have proposed an algorithm that uses a K-means clustering algorithm in order to generate clusers of APs (which can be part of multiple clusters), then a single-layer neural network is train as a zone classifier that divides the main areas in smaller parts and finally the SVM (Support Vector Machine) estimates an user’s position based on the received signal strength. This innovative multi-step approach has proven to work great in the test area, having an estimation error of only 1.3m.

Another RSSI fingerprinting localization method, WiDeep [18], is proposed by M. Abbas, M. Elhamshary, H. Rizk, M. Torki and M. Youssef. In this approach, they are trying to minimize the signal strength difference caused by using different smartphones by using a deep learning model that uses stacked denoising autoencoders to capture the relation between the WiFi scans and the fingerprints from the database. After this process, a regularization technique is applied in order to make the algorithm better for different kinds of scenarios, resulting in a mean estimation error of 2.64m.

P. Dai, Y. Yang, M. Wang și R. Yan [19] are proposing another multi-model approach of the positioning estimation using RSSI fingerprints. Using this approach, in the preprocessing phase, the zone is first divided into different zones, based on the longitude and latitude. In the next step, the obtained data is fed to a deep neural network that will be used to classify the zone where a new signal reading is registered. Then, by knowing the specific area, a weighted k-nearest neighbor algorithm is applied to estimate the user’s position, resulting in an estimation error of only 1.67m.

In the case of PDR (Pedestrian Dead Reckoning), where only inertial sensors data from a smartphone are used, M. Zhang, Y. Wen and J. Chen [20] have developed a system that uses a feed-forward neural network with applied extreme learning processes that improve the network’s learning speed, which takes as input sequential information from the accelerometer, magnetometer and gyroscope in order to estimate an user’s movement habits. This experiment shows the possibilities of using IMU-only dead reckoning algorithms, arriving to a mean estimation error of only 1.7m.

Another approach of using only inertial sensors data has been shown by A. Poulouse, O. Eyobu and D. Han [21], where different methods of calculating the pitch and roll of the smartphone using formulas that take in consideration the phone’s accelerometer data, then the results are used in order to detect the person’s step length and direction, arriving at an estimation error of 2.6m, without using machine learning positioning methods.

Finally, in their paper, W. Xijia, W. Zhiqiang and V. Radu [22] are proposing a multimodal approach, MM-Loc, that uses the inertial sensors of the martphone and the received WiFi signal strength. In the first step of the process, the sequential accelerometer, gyroscope and magnetometer data is used to train a recurrent neural network with a LSTM and the RSSI fingerprints are used to train a deep neural network in order to estiamte the user’s position. Because the data frequency is higher for the inertial sensors, the LSTM model is used most of the time, but when WiFi readings are available, the 2 model’s results are aggregated in order to increase the positioning accuracy. Using this approach, the model has managed to obtain an estimation error of 1.8m on datasets from 2 universities.

Taking into consideration the available data, the accuracy results and the difficulty of implementation, 2 algorithms have been chosen to be implemented and optimized. The first one, similar to [19], will leverage a deep neural network architecture combined with k-nearest neighbour in order to estimate an user’s location based on the WiFi signal readings. In the second one, based on the research done by W. Xijia, W. Zhiqiang and V. Radu [22], we will implement an LSTM model that will estimate the position based on sequential inertial sensors data.

# METHODOLOGY

In this chapter will be presented the used datasets, an overview of how deep neural networks and k-nearest neighbour can be used for location estimation based on WiFi data and how recurrent neural networks can be implemented for pedestrian dead reckoning.

## Datasets

For the training and implementation of the WiFi-based indoor localization algorithm, it was required to obtain a large enough RSSI fingerprints dataset, having also the latitude and longitude of the device at the scanned locations. In this manner, for the first iterations, the ”UJIIndoorLoc” dataset [23] has been used, it being a cluster of WiFi scans from 3 buildings of the Jaume I university, covering 13 total floor. The data is divided in 2 parts, the first one being the training set (19937 entries) and the validation set (1111 entries), each row consisting of 524 attributes, as follows (Figure 3):

* Attributes 0-520: RSSI from the Aps, measured in dBm (lowest value is -104 dBm, the APs where no signal is detected have the value 100)
* Attribute 521: Longitude
* Attribute 522: Latitude
* Attribute 523: The floor
* Attribute 524: The building

Table

Description automatically generated

Figure 3. UJIIndoorLoc dataset structure

With the goal that in the future a multimodal approach of indoor localization that could use both WiFi and inertial readings in real time will be implemented, it has been decided to also use a time series dataset that could be used for training the models for each type of sensors. In this manner, the “PrecisLoc” [24] has been chosen, it being a sequential time series cluster of scans registered inside the PRECIS building of the “University POLITEHNICA of Bucharest”. The data collection has taken place at the 6th and 7th floor, covering different scenarios and moving patterns, including walking, climbing stairs, using the elevator, etc. The data was collected using a Xiaomi Mi A1 phone with the Android 8.1 operating system, through a special application that allowed the recording and storage of data from the sensors, together with the manual addition of the exact position of the user.

The data set is composed of 5 different scenarios, each with additional displacements compared to the previous scenario. In the current experiments, scenario 1 was chosen as the reference system, where a person exits a room, moves through adjacent hallways, enters a 2nd room which he circles, then exits and moves in a straight line to the first room (Figure 4).

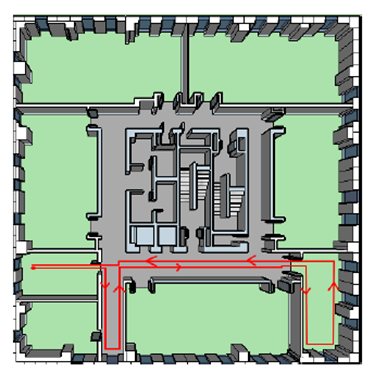


Figure 4. Trajectory of the scenario 1 [24]

The chosen scenario has in its composition several sub-folders, organized in time periods (being recorded at different times of the day), which contain the records of the devices used. For the research presented in this paper, the following files were used:

* ground\_truth.xml: this file contains the latitude (lat) and the longitude (long) at a certain time period, for the purpose of correlation with recorded signals (Figure 5);

A screen shot of a computer

Description automatically generated with low confidence

Figure 5. Example of data from ”ground\_truth.xml”

* Sensor\_readings.xml: this file contains the registered sensor data, along with the "st" timestamp when it was recorded. In Figure 6 can be seen the values ​​of the signals from the gyroscope (g), magnetometer (m) and accelerometer (a) on all their axes (x, y, z), together with the values ​​of the wifi signal received from the access points "b".

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Description automatically generated

Figure 6. Example of data from ”Sensor\_readings.xml”

## WiFi signals localization algorithm overview

Similar to the work of P. Dai, Y. Yang, M. Wang și R. Yan [19], for the indoor localization based on WiFi data, an ensemble model approach has been chosen, combining 2 machine learning algorithms, the first one being used in order to classify the data on key reference areas, the second having the role of estimating the position of a person taking into account the classification made in the previous stage.

### Deep neural networks

Artificial neural networks represent systems designed to imitate the human brain, formed by groups of nodes connected to each other. Deep neural networks are artificial neural networks that have input and output layers, but also multiple hidden layers in between (Figure 7).

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Description automatically generated

Figure 7. Deep Neural Network architecture (image taken from [25])

### K-nearest neighbor

The KNN algorithm is a supervised learning algorithm that can be both used for classification or regression problems by calculating the proximity of an element to the other values in the dataset. It’s most common use cases include data preprocessing, credit and finance estimation, health areas and pattern recognition. This algorithm doesn’t undergo a training stage, but stores the training data, meaning that the most processing power is needed at the prediction or classification level.

In order to be able to determine the closest points to a certain value, the distance between it and its neighbors must be calculated for aggregatin the data into the right region. The main distances used are Euclinidan (ecuation 1), Manhattan (ecuation 2) and Minkowski (ecuation 3).

|  |  |  |
| --- | --- | --- |
|  |  | (1) |

|  |  |  |
| --- | --- | --- |
|  |  | (2) |

|  |  |  |
| --- | --- | --- |
|  |  | (3) |

### Proposed model

In the first stage of the process, a deep neural network was trained to classify the room from which the data was transmitted. The neural network consists of an input layer, 2 hidden learning layers and an output layer.

In the second stage of the process, the implementation of a weighted KNN model was realized. Having the prediction of the room from the previous step, the final position estimation has been optimized by using as input data for the new model only those locations that correspond to the room where the data is supposed to have been captured (Figure 8).

A picture containing text, diagram, screenshot, line

Description automatically generated

Figure 8. The architecture of the WiFi localization model, similar to [19]

## Inertial sensors localization algorithm overview

Pedestrian dead reckoning represents the process of estimating a person’s position based on the previous movements, starting from a known location. Similar to this process, a recurremt neural network takes as input sequential data, memorizing previous steps in order to make predictions better than a normal feed forward neural network by not relying only on the new given values.

A recurrent neural network is a special type of artificial neural network that is created specifically for issues that need continuous sequential data in order to generate new estimates, such as stock prices predictions, language translation and speech processing [26]. The power of a RNN is leveraged by its architecture, wich creates a link between the neurons from the previous layers and the ones from the current layer, making it use historic data in order to generate new predictions. In this way, the model could use the previously registered inertial sensors values in order to generate an estimate of the current location. The structure of an RNN is shown in Figure 9.

A picture containing circle, diagram, green, design

Description automatically generated

Figure 9. Unfolded RNN architecture over time, image taken from [27]

Training an RNN is done by measuring the deviation between the predicted values and the real ones, by defining a loss function that can calculate this difference. The input data is passed through multiple hidden layers, then the output is predicted. Once a cycle is finished, the loss function is calculated and passed backward in order to train the next iteration, propagating the gradients in the process. This can cause problems such as the exploding gradients (where the propagated gradients are too big), or the vanishing gradients (where they are too smal), this causing the historic data to have too much or too litle importance compared to the newer values.

In order to avoid the previously described issues, new RNN models have been developed over time, one of which being the LSTM (Long-Short Term Memory), specially designed in order to learn using long-term dependencis, solving the vanishing and exploding gradients problems by adding extra logic to the model (Figure 10).

A picture containing screenshot, diagram, line, cartoon

Description automatically generated

Figure 10. Architecture of a LSTM model, image taken from [28]

In the first step, called the ”forget gate” [28], it is decided how much of the historic data should be kept in order to calculate the current step. This is done by taking the previous long-term data and multiplying it with the result of a sigmoid function (which is based on the current value of the input) that ranges between 0 and 1, where 1 represents a full keeping of data and 0 means that all the historic data will be forgotten (formula 4, where represents the output of the sigmoid function , represents the weight of the current input and the short-term memory from the previous step and is the bias.

|  |  |  |
| --- | --- | --- |
|  |  | (4) |

In the second step, called the ”input gate”, the value of the new potential long-term memory based on the current values is calculated. This is done by aplying a sigmoid function on the sum of the short-term memory and input data (formula 5), then multiplying this value with the result of a hyperbolic tangent function applied to the same sum (formula 6). The result of this process is then added to the long-term memory calculated in the first step.

|  |  |  |
| --- | --- | --- |
|  |  | (5) |

|  |  |  |
| --- | --- | --- |
|  |  | (6) |

In the third and last step, called the ”output gate”, a sigmoid function is used to decide what part of the cell’s current state it’s goind to be used for the output (formula 7). The data obtained is then multiplied with the result of a tanh function applied on the long-term memory value (formula 8), resulting in the output value of the short-term memory of the current cell (formula 7).

|  |  |  |
| --- | --- | --- |
|  |  | (7) |

|  |  |  |
| --- | --- | --- |
|  |  | (8) |

Using the aforementioned LSTM model, the program will be able to estimate an user’s current location based on the historic sequential data coming from the inertial sensors, by updating its state based on the accelerometer, gyroscope and magnetometer readings fluctuations.

# IMPLEMENTATION

## Data preprocessing

In order to train the previously described models, the available datasets had to be processed to adhere to certain forms which could be fed as inputs for the neural networks.

### UJIIndoorLoc dataset processing

For the first iteration of the localization algorithm based on WiFi signals, it has been decided that the UJIIndoorLoc dataset should be utilized, as it is the most used in the specialty literature focused on the indoor positioning methods that are using fingerprints, thus also having a comparison benchmark between the existing solutions and the ones presented here.

In order to increase the accuracy of the model, it was decided to use only one building out of the 3 present in order to eliminate a part of the access points from where an ordinary user would not be able to capture a signal. Following this idea, it was found that the most values ​​were recorded in building number 3, which also has 5 floors, while the other buildings have 4 floors (Figure 11).

Chart, bar chart

Description automatically generated

Figure 11. Distribution of buildings and floors

Following the previous decisions, a processed data set containing approximately 9500 entries of 529 columns was obtained, which were then divided into 80% training data and 20% test data.

For the first stage of the algorithm (DNN classification), the model features are represented by the WLAN signal strengths, while the target value is the floor from which those values ​​are assumed to have been captured. As an initial step, the data was scaled in the interval [0, 1] to standardize the independent characteristics and thus increase the accuracy of the model (Figure 12).

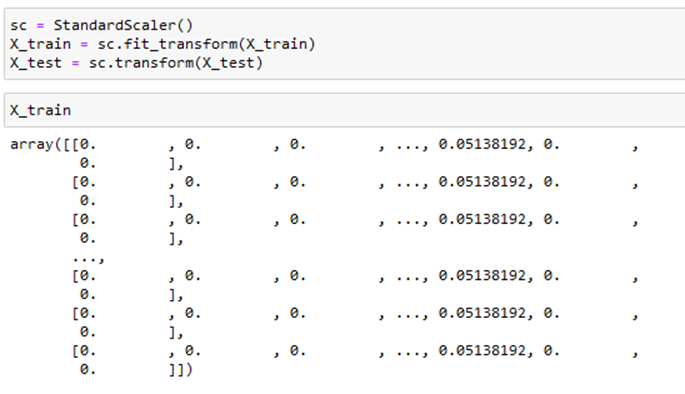


Figure 12. Scaling of the independent features

In the second stage of the model implementation, only those values ​​belonging to the floor obtained in the previous step are extracted from the training data, these being used as inputs of the weighted KNN model, in order to take into account the points closest to the real position.

### PrecisLoc dataset processing

In order to train the models on data that is closer to the real world scenarios, it was decided to use a second dataset, which would have both WiFi and inertial sensors data, taken in real time by an user while traveling inside a building. The details of this dataset have been covered in the chapter 3.

The first step in converting the data to the right format was to transform it from “.xml” files intro “.xcv” files. In order to do so, a Python script which could read the raw file and manipulate them into the proper format has been created.

## WiFi signals localization algorithm

## Inertial sensors localization algorithm

Diagram, schematic

Description automatically generated

Figure 8. DNN architecture, similar to [19]

The first layer, that of the input data, consists of 41 neurons (SPUS SI DE PRIMUL ALGORITM?), equal to the number of characteristics of each input (the number of total Access Points). The output layer is formed of 4 neurons that represent the room of the total area where the data is estimated to have been registered in.

# RESULTS

TODO:

* Reszultate algo 1
* Rezultate algo 2

# CONCLUSIONS

TODO:

* concluzii

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