Positioning System Project With GPS-WiFi-INS Fusion

Elif Beray SARIISIK, Orhan Eren BICAKCI

Telecom Sudparis/ IP Paris

Paris, France

elif-beray.sariisik@telecom-sudparis.eu

orhan-eren.bicakci@telecom-sudparis.eu

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I. Introduction

In this report, the analysis and synthesis of indoor positioning system by combining the methods of GPS-WiFi-INS is made. The purpose of this report is to provide a technique to succesfully achieve indoor positioning in the building A in Telecom Sudparis with GPS-WiFi-INS fusion. The building A consists of 4 floors. However, the measurement is mostly made on the third floor of the building A due to the convenience to access to the rooms. Furthermore, additional measurement is, likewise, handled on the second floor in order to observe the difference of the Received Signal Strength (RSS) due to the change in the floors to acquire a technique to estimate the other two floors. Several devices are utilized so as to acquire data of both WiFi and INS such as MacBook Air, Iphone, and Samsung mobilephone to assess the results throughoutly.

After realizing the fact that RSS measurements are not enough to obtain the exact indoor position, several inertial sensors which are accelometer and gyroscope are utilized to estimate the trajectory to estimate the exact location.

II. Methodology

In the methodology part of the project, several steps are followed to investigate the problematic so that comprehensive solution can be implemented. Firstly, the environment and the usage of the sensors are determined in order to continue with the theoretical synthesis of the sensors.

i. Investigation of the Floor Plans of the Building A

Firstly, the floor plans of the building A is investigated to locate the each access point on each floor for measuring the relative distance of a certain point to access point.

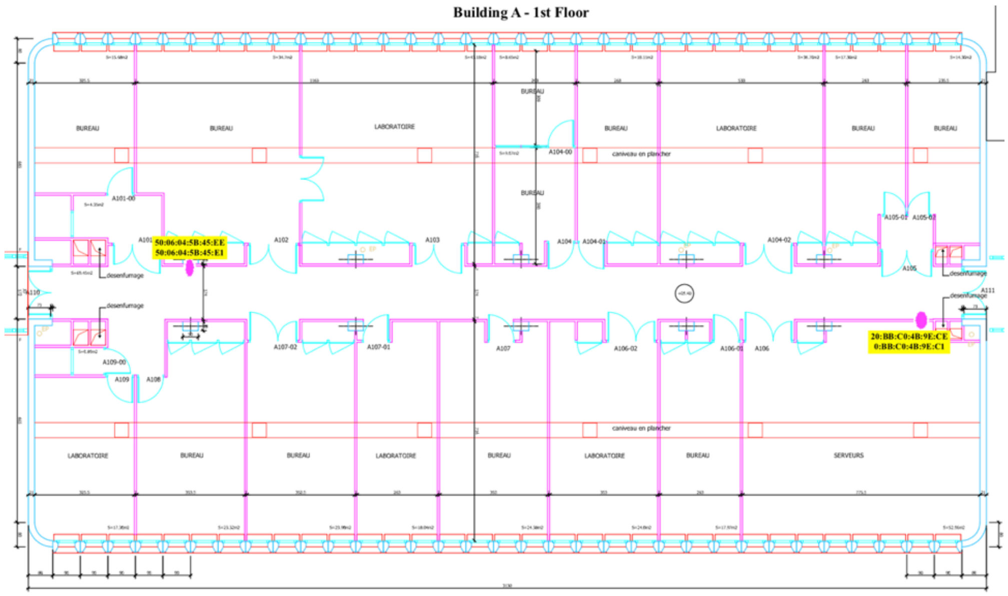

Figure 1: The Floor Plan of the Building A 1st Floor with Access Points are highlighted

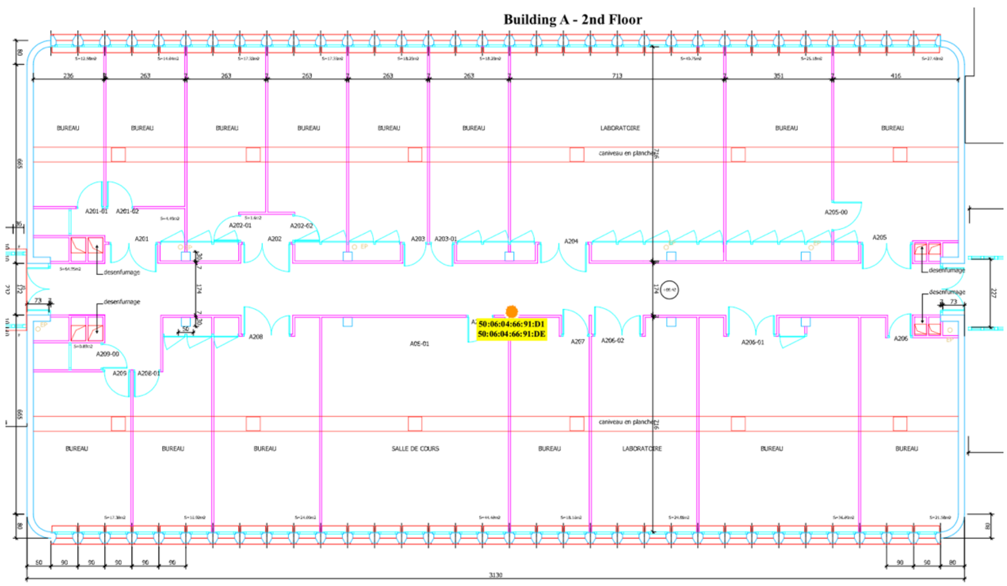

Figure 2: The Floor Plan of the Building A 2nd Floor with Access Points are highlighted

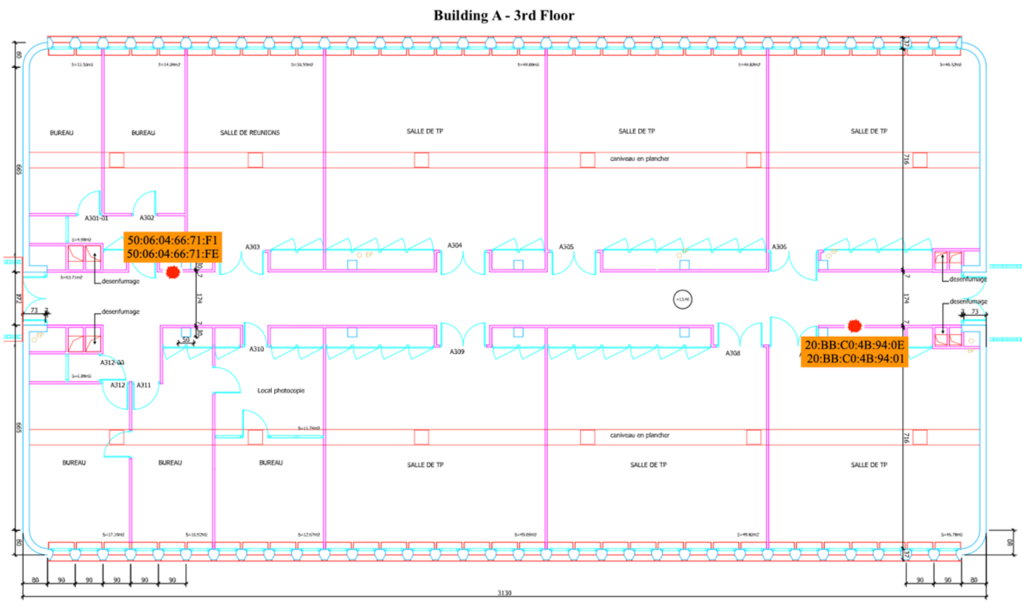

Figure 3: The Floor Plan of the Building A 3rd Floor with Access Points are highlighted

ii. Research for utilities to retrieve the WLAN signal levels

Secondly, the application which is utilized in order to take RSS measurement is determined by going through several application to find out with highest sampling rate.

In order to observe the WLAN signal levels, several applications are used, such NetSpot, Airport Utility. Nonetheless, Airport Utility is decided to finalize our measurement since its capability of sampling at 0.33Hz enables us to take several datas in a minute so that we can analyze the mean and the variance of the system. Airport Utility is used on Iphone 14 Pro Max which has the Wi-Fi module of Wi-Fi 6E, which enables us to take more accurate values. The .txt files exported from the application is observed as Figure 4.

a301.5.txt

```
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"eduroam", "50:06:04:5B:3E:21", "-89", "1", "11:47:45"
"eduroam", "50:06:04:5B:3E:21", "-89", "1", "11:47:48"
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"eduroam", "50:06:04:5B:3E:21", "-90", "1", "11:48:00"
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"eduroam", "20:BB:C0:4B:94:0E", "-61", "52", "11:47:39"
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"eduroam", "20:BB:C0:4B:A2:3E", "-91", "48", "11:47:30"
```

Figure 4: An Example .txt File taken out from Airport Utility

After investigating that RSS values rapidly changes even in 3 seconds, we decided to take a mean and variance of bunch of RSS measurement so that we can succesfully represents each rooms data more easily. Therefore, a python code is implemented in order to extract mean and variances more easily (see Appendix A).

iii. Maximum Likelihood (ML) Estimation

To determine the specific room a person is located in, we employ Maximum Likelihood (ML) estimation to assess the likelihood of each room based on available data. This involves calculating the probability that the observed signal characteristics, such as Wi-Fi signal strength or other sensor inputs, correspond to each room. By comparing these probabilities, we can identify which room most likely matches the observed data. The process concludes by selecting the room with the highest likelihood, thus identifying the room that best fits the test value provided. This method ensures an accurate and reliable determination of the person's location within the premises.

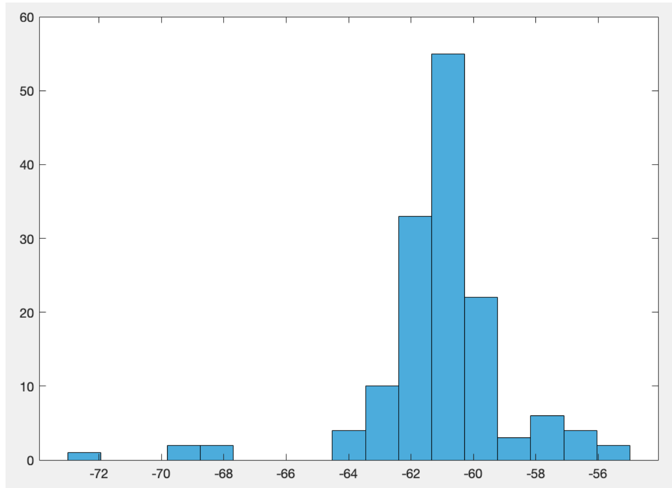

Figure 5: An Example of 4-Minute RSS Measurement indicating that Gaussian Function is obtained in limit as t goes to infinity

The graph of the 4 minute RSS Measurement is investigated to decide on the probabilistic model which can represent our data. It is found that after taking several measurement, the shape of the graph behaves as a gaussian pdf. Thus, the multivariate Gaussian probability density function is used to compute the room likelihood. The equation used to compute the multivariate Gaussian probability is:

$$p(x; \mu, \Sigma) = \frac{1}{(2\pi)^{n/2}|\Sigma|^{1/2}} \exp\left(-\frac{1}{2}(x-\mu)^T\Sigma^{-1}(x-\mu)\right)$$

We compute the room likelihoods by using MATLAB simulation because of easiness in usage of probabilistic models.

iv. Usage of Additional Sensors: Accelometer and Gyroscope

RSS (Received Signal Strength) measurements alone proved insufficient for accurately determining the exact indoor position of an object. To enhance indoor positioning accuracy, accelerometer and gyroscope sensors are utilized to estimate the object's trajectory. By tracking motion and orientation changes, these sensors provide crucial data that complements RSS measurements.

To gather comprehensive data, two mobile phones are simultaneously employed, each collecting accelerometer and gyroscope readings. The application Phyphox is used to facilitate this process, allowing for precise data acquisition and analysis. This combined approach significantly improves the accuracy of indoor positioning by leveraging the strengths of both RSS measurements and inertial sensor data.

v. Implementing MATLAB Step Counter and Turn Counter for trajectory estimation

After analyzing the data from the accelerometer and gyroscope, we implement a step counter and a turn counter by utilizing MATLAB software (see Appendix C) to estimate the trajectory taken. The accelerometer data helps identify each step taken by detecting repetitive motion patterns, while the gyroscope data detects changes in orientation and direction. By counting the number of steps and turns, we can reconstruct the path traveled with greater accuracy.

This method allows us to map the trajectory by correlating the sequence of steps and turns, providing a detailed estimation of the movement within the indoor environment. This approach enhances indoor positioning by leveraging precise motion and orientation data.

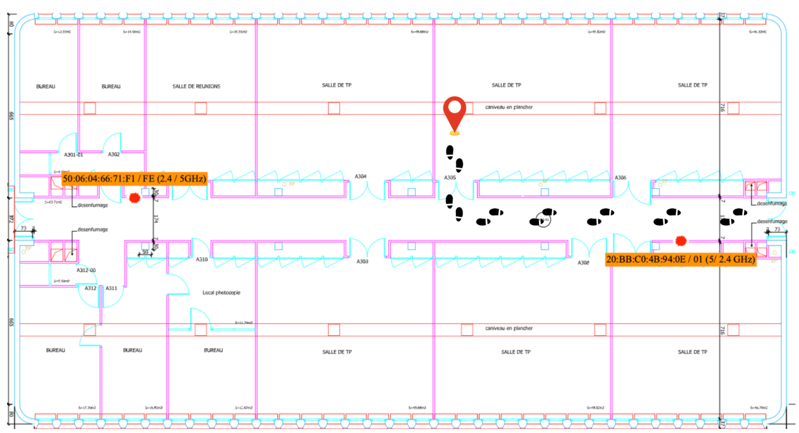

Figure 6: An Example of Trajectory Estimation occupied by usage of INS

vi. Sensor Fusion

Overall, achieving exact indoor positioning requires combining RSS measurements with data from the accelerometer (Acc) and gyroscope (Gyro) through sensor fusion. RSS measurements can determine the specific room a person is in by analyzing signal strength from various access points. Meanwhile, Acc and Gyro data provide a detailed estimate of the trajectory taken by tracking steps and turns. Sensor fusion integrates these two data sources, allowing us to leverage the strengths of each method. This process enables us to pinpoint not only the room but also the precise path traveled within it. By using sensor fusion, we achieve a comprehensive solution for accurate indoor positioning and movement tracking, significantly enhancing the reliability and precision of indoor navigation systems.

III. Measurements

In the measurement part of the project, both environmental and sensor measurements are taken to implement the basis of the project.

i. Environmental Measurements

Environmental measurements are taken in order to visualize a relative distance between the access points and the location of a person. The provided floor plans include the square meter measurements for each room (see Figure 1, Figure 2, and Figure 3). Additionally, the corridor length is specified as 29.70 meters. An investigation has been conducted on the 1st, 2nd, and 3rd floors to gather data and make accurate estimations for the measurements of the other floors. This investigation involves analyzing the layout, room dimensions, and corridor lengths on these floors to develop a comprehensive understanding of the building's overall structure and spatial distribution. By comparing these floors, it is possible to extrapolate and estimate the measurements for the remaining floors, ensuring consistency and accuracy in the assessment of the building's total area and design.

Nevertheless, the environmental measurements were not directly implemented by using propagation models provided by the project proposal since RSS values are changing rapidly so that the implementation by propagation models cannot be implemented successfully.

ii. Sensor Measurements

Three sensor measurements which are Received Signal Strength, Accelometer, and Gyroscope, are taken in order to utilize the method described in the methodology part.

a. RSS Measurements

In order to increase the precision of the RSS measurements, three access points operating on both 2.4 GHz and 5 GHz frequencies are utilized. Data from each access point is collected over a 2-minute period at a sampling rate of 0.33 Hz. This data is then used to calculate the mean and variances for each access point in order to impelement a probablistic model of RSS measurements, providing a statistical basis for determining the most accurate location estimate.

After collecting the data, a python code provided in the Appendix A part is implemented to extract mean and variance of the 2-minute length data. This procedure is done for every room on third floor of the Building A (see Table 1-16). Moreover, the measurement of both the closest location to the door and the farthest location to the door of the rooms, which we have permission to take a comprehensive data, is taken in order to both observe the effect of the environment in a room and increase the sensitivity of our estimation. Therefore, some measurement table is named as A'room number' 'front' or 'back' to indicate the location that measurement is taken.

ID of Access Point	Mean of RSS	Variance of RSS	Corresponding Access Point
351	-48.14	7.66	FE
352	-64.41	4.79	OE
251	-90.00	0.01	DE
322	-61.36	11.86	O1
321	-46.68	1.85	F1
221	-81.28	3.20	D1

Table 1: The Table for RSS Measurements of the Room A301

ID of Access Point	Mean of RSS	Variance of RSS	Corresponding Access Point
351	-51.83	4.81	FE
352	-65.58	4.74	OE
251	-81.79	2.91	DE
322	-78.52	12.67	O1
321	-53.83	15.06	F1
221	-74.13	22.11	D1

Table 2: The Table for RSS Measurements of the Room A303 Fro

ID of Access Point	Mean of RSS	Variance of RSS	Corresponding Access Point
351	-52.37	1.83	FE
352	-62.73	3.53	OE
251	-83.77	0.45	DE
322	-71.57	4.38	O1
321	-58.03	11.30	F1
221	-76.11	0.81	D1

Table 3: The Table for RSS Measurements of the Room A303 Back

ID of Access Point	Mean of RSS	Variance of RSS	Corresponding Access Point
351	-57.95	2.41	FE
352	-54.41	1.24	OE
251	-75.86	2.30	DE
322	-58.29	4.20	O1
321	-58.59	24.51	F1
221	-70.36	7.96	D1

Table 4: The Table for RSS Measurements of the Room A305 Front

ID of Access Point	Mean of RSS	Variance of RSS	Corresponding Access Point
351	-73.86	5.15	FE
352	-71.28	1.58	OE
251	-80.90	1.20	DE
322	-68.59	3.48	O1
321	-64.59	8.31	F1
221	-77.45	20.52	D1

Table 5: The Table for RSS Measurements of the Room A305 Back

ID of Access Point	Mean of RSS	Variance of RSS	Corresponding Access Point
351	-57.29	1.74	FE
352	-51.94	2.76	OE
251	-86.42	0.24	DE
322	-45.00	4.24	O1
321	-56.88	7.99	F1
221	-79.59	2.24	D1

Table 6: The Table for RSS Measurements of the Room A306 Front

ID of Access Point	Mean of RSS	Variance of RSS	Corresponding Access Point
351	-61.39	14.81	FE
352	-57.29	3.99	OE
251	-93.00	0.01	DE
322	-56.79	4.31	O1
321	-66.46	21.18	F1
221	-87.05	11.95	D1

Table 7: The Table for RSS Measurements of the Room A306 Back

ID of Access Point	Mean of RSS	Variance of RSS	Corresponding Access Point
351	-63.41	2.15	FE
352	-57.82	2.51	OE
251	-86.59	2.36	DE
322	-48.95	4.32	O1
321	-61.77	2.63	F1
221	-82.95	1.95	D1

Table 8: The Table for RSS Measurements of the Room A307 Front

ID of Access Point	Mean of RSS	Variance of RSS	Corresponding Access Point
351	-77.48	2.73	FE
352	-66.84	2.29	OE
251	-88.00	0.01	DE
322	-67.24	20.66	O1
321	-73.92	9.75	F1
221	-91.12	7.71	D1

Table 9: The Table for RSS Measurements of the Room A307 Back

ID of Access Point	Mean of RSS	Variance of RSS	Corresponding Access Point
351	-64.86	5.91	FE
352	-51.89	0.67	OE
251	-83.13	0.46	DE
322	-47.82	3.00	O1
321	-54.00	4.86	F1
221	-80.32	15.36	D1

Table 10: The Table for RSS Measurements of the Room A308 Front

ID of Access Point	Mean of RSS	Variance of RSS	Corresponding Access Point
351	-81.72	1.88	FE
352	-67.28	0.76	OE
251	-84.68	3.26	DE
322	-67.88	19.23	O1
321	-75.44	5.53	F1
221	-74.40	7.12	D1

Table 11: The Table for RSS Measurements of the Room A308 Back

ID of Access Point	Mean of RSS	Variance of RSS	Corresponding Access Point
351	-53.08	17.99	FE
352	-54.92	20.30	OE
251	-76.88	4.79	DE
322	-55.85	12.21	O1
321	-55.58	13.24	F1
221	-70.62	6.16	D1

Table 12: The Table for RSS Measurements of the Room A309 Front

ID of Access Point	Mean of RSS	Variance of RSS	Corresponding Access Point
351	-73.05	1.13	FE
352	-72.18	3.06	OE
251	-84.50	1.70	DE
322	-71.50	3.34	O1
321	-65.73	1.93	F1
221	-76.45	9.98	D1

Table 13: The Table for RSS Measurements of the Room A309 Back

ID of Access Point	Mean of RSS	Variance of RSS	Corresponding Access Point
351	-53.54	3.94	FE
352	-63.81	5.08	OE
251	-80.85	5.98	DE
322	-57.12	8.49	O1
321	-46.54	8.33	F1
221	-74.80	15.00	D1

Table 14: The Table for RSS Measurements of the Room A310

ID of Access Point	Mean of RSS	Variance of RSS	Corresponding Access Point
351	-56.00	3.30	FE
352	-80.00	2.10	OE
251	-83.05	5.45	DE
322	-74.32	5.37	O1
321	-49.83	6.03	F1
221	-83.05	5.45	D1

Table 15: The Table for RSS Measurements of the Room A311

ID of Access Point	Mean of RSS	Variance of RSS	Corresponding Access Point
351	-54.88	2.27	FE
352	-80.56	3.85	OE
251	-84.96	1.79	DE
322	-63.50	8.67	O1
321	-50.24	11.38	F1
221	-84.96	1.90	D1

Table 16: The Table for RSS Measurements of the Room A312

After obtaining the measurements, the MATLAB implemented for the room likelihood estimation is utilized (see Appendix B). Several measurements from different rooms are tested to improve the algorithm. An example test data is taken from the room A303 as x = [-47; -63; -90; -91;-45; -79] and inputted into the algorithm. The result of the simulation is obtained as intended (see Figure 7 and Figure 8). The classification of the maximum likely room to minimum likely room is displayed to observe the other rooms that the algorithm detects to investigate and estimate the position of the person more precisely (see Figure 8).

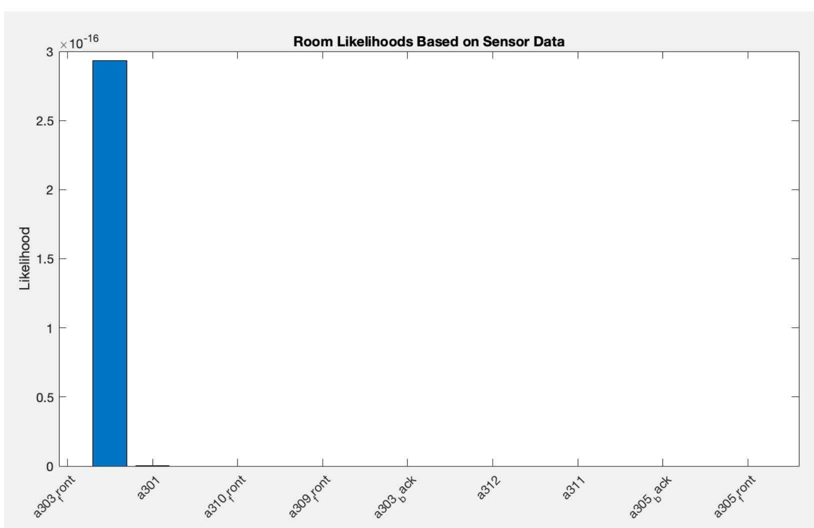

Figure 7: The Graph of the Output of the Room Likelihood Simulation Given a Test Data from A303

```
>> rfprojectwirelesspart
  Columns 1 through 6

    {["a303_front"]}    {["a301"]}    {["a310_front"]}    {["a309_front"]}    {["a303_back"]}    {["a312"]}

  Columns 7 through 11

    {["a311"]}    {["a305_back"]}    {["a305_front"]}    {["a307_front"]}    {["a306_front"]}

  Columns 12 through 16

    {["a308_back"]}    {["a307_back"]}    {["a308_front"]}    {["a309_back"]}    {["a306_back"]}

>>
```

Figure 8: The Command Line of the Output of the Classification of the Room Likelihoods from Maximum Likely to Minimum Likely

After verifying that the algortihm of the room likelihood is succesfull, the RSS measurements are made in motion to investigate whether the trajectory estimation can be made by using only RSS measurement (see Figure 9). It is observed that only the start and the end points of the trajectory can be exactly obtained by utilizing RSS data. However, we cannot retrieve an information about the trajectory taken by the person whether it is a direct walking or running or walking in circular motion.

Consequently, other sensors should be implemented so that the trajectory taken by the person is succesfully estimated. That's why, the INS which are accelometer and gyroscope is utilized with this project to acquire the exact indoor positioning of a person.

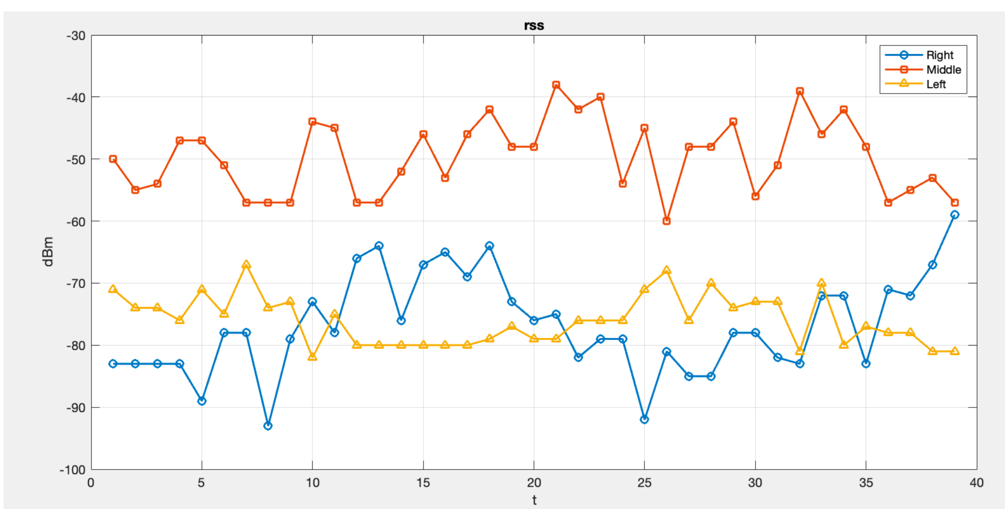

Figure 9: RSS Measurement of 2nd Floor A.P (red), 3rd Floor A.P. ending with F1 / FE (yellow), and 3rd Floor A.P. ending with 01 / 0E (blue)

b. Accelometer Measurements

The data of the sensor of accelometer is taken and investigated on MATLAB simulation. After plotting the data to investigate the peaks for step counter, it is found that the inputted data was so noisy. Therefore, an algorthim is implemented to filter the data so that we can count the steps of the person.

The algorithm processes acceleration data to estimate step frequency and count from sensor recordings. Initially, the data is read and converted into an array, extracting time series and acceleration components. The magnitude of acceleration is calculated, and its mean is subtracted to center the data, followed by squaring to highlight variations.

A moving mean filter smooths this centered squared data. The smoothed data is then segmented into 5-second windows, appending zeros as necessary to ensure consistent window sizes. Each windowed segment undergoes a Fast Fourier Transform (FFT) to convert the data from the time domain to the frequency domain. For each window, the peak frequency component is identified, corresponding to the dominant frequency of the signal, presumed to be related to the step frequency.

The total number of steps is estimated by summing the peak frequencies across all windows and multiplying by five. Finally, the results are visualized to show both the time-domain data and its frequency-domain representation for a selected window. This algorithm effectively combines time-domain processing, smoothing, windowing, and frequency-domain analysis to extract step frequency information from acceleration data.

On Figure 10, you can the graph of the output windowed data for counting step which is indicated as the blue graph.

After utilizing the accelometer, the step of the person succesfully counted. However, whether the person has changed his/her direction or not is not obtained with the accelometer data. Therefore, the trajectory estimation is not fullfilled by only using the accelometer data whereas by combining with the gyroscope data, the trajectory estimation can be fulfilled.

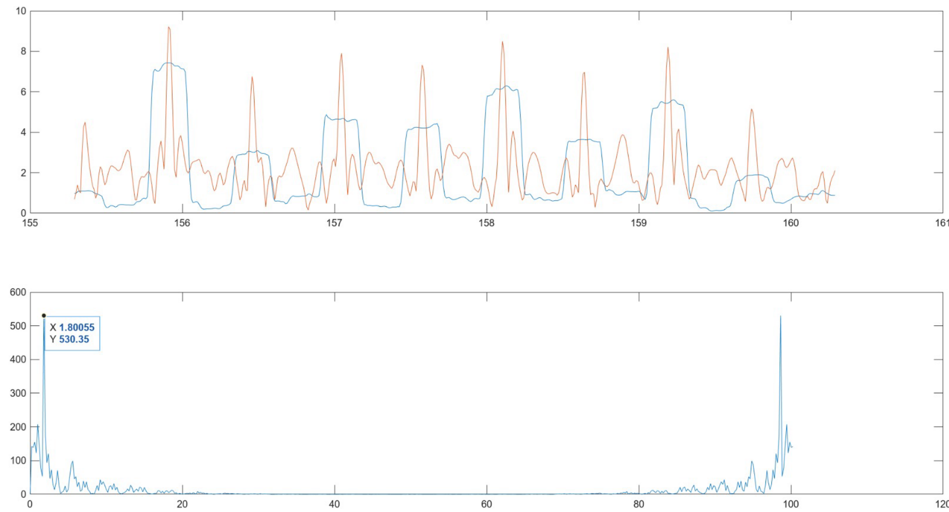

Figure 10: The Graph of Accelometer Raw Data (Red) and Windowed Accelometer Data (Blue) used for Step Counter on Upper Figure. The Lower Figure represents the Corresponding Frequency Domain

c. Gyroscope Measurements

After obtaining the gyroscope measurements, it is observed that the noise in the gyroscope measurements are less compared to accelometer measurements. Therefore, the coding background and the algorthim is easily implemented compared to accelometer. Firstly, a turn counter is implemented by simulatenosly assesing the magnitude of the data so that the direction that the person is forwarding is also obtained (see Figure 11).

The algorithm processes gyroscope data to detect and analyze rotational movements from sensor recordings. Initially, gyroscope data is read and converted into an array, extracting time series and gyroscope components. The magnitude of the gyroscope signal is calculated, and the z-component is smoothed twice using moving mean filters with different window sizes. The squared smoothed signal highlights significant peaks, which are detected based on their height relative to the average value of the squared signal. Each detected peak indicates a rotational movement, with the direction determined by the sign of the smoothed signal at the peak locations, represented as complex numbers. The times of these peaks are recorded to provide the exact moments of the rotations.

After observing the result, the direction and turn is detected by this algorithm. For an illustration, see Figure 11.

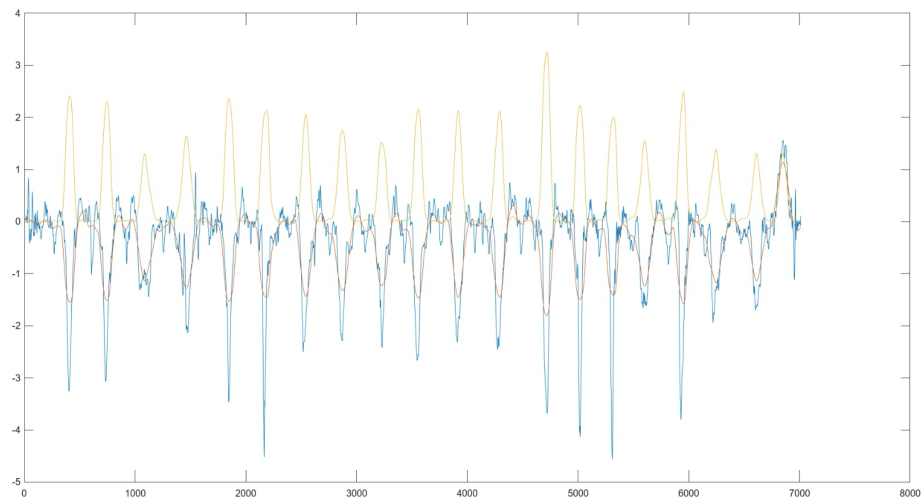

Figure 11: The Graph of Gyroscope Raw Data (Blue), Final Gyroscope Data (Yellow), and Intermediate Gyroscope Data for turn direction (Red) used for Turn Counter

IV. Synthesis: Sensor Fusion

In the synthesis part, namely sensor fusion, the all sensor measurements and simulations are collected and proccessed simultaneosly for achieveing comprehensive indoor positioining. Firstly, the data from the accelerometer and gyroscope is collected simultaneously to provide comprehensive motion information.

These inertial sensor (INS) readings are then combined sequentially with Received Signal Strength (RSS) measurements. This integration allows for the enhancement of location estimation and motion tracking by leveraging the complementary strengths of both sensor types. The accelerometer and gyroscope data provide detailed motion dynamics, while the RSS measurements contribute to position accuracy, resulting in a more robust and precise tracking system.

In order to visualize the sensor fusion, an example testing is performed to investigate the simulations performance. Firstly, accelometer and gyroscope data is taken without having information about the step size and the speed of the person. These INS data are simulated with the algorithm provided in Appendix C and Appendix D. The output results of this measurement is obtained as Figure 12 and Figure 13. The step counter and the turn counter is achieved succesfully. It is realized that the trajectory estimation without the knowledge of RSS measurements provides different paths for different step sizes and speed (see Figure 14).

Therefore, it is proven that RSS measurements as well as INS measurements are required to achieve indoor positioning. Consequently, RSS measurements are made and it is observed that the room likelihood estimation states that the room A309 is the most likely room where the person can be positioned, which is coincides with our measurement results (see Figure 15).

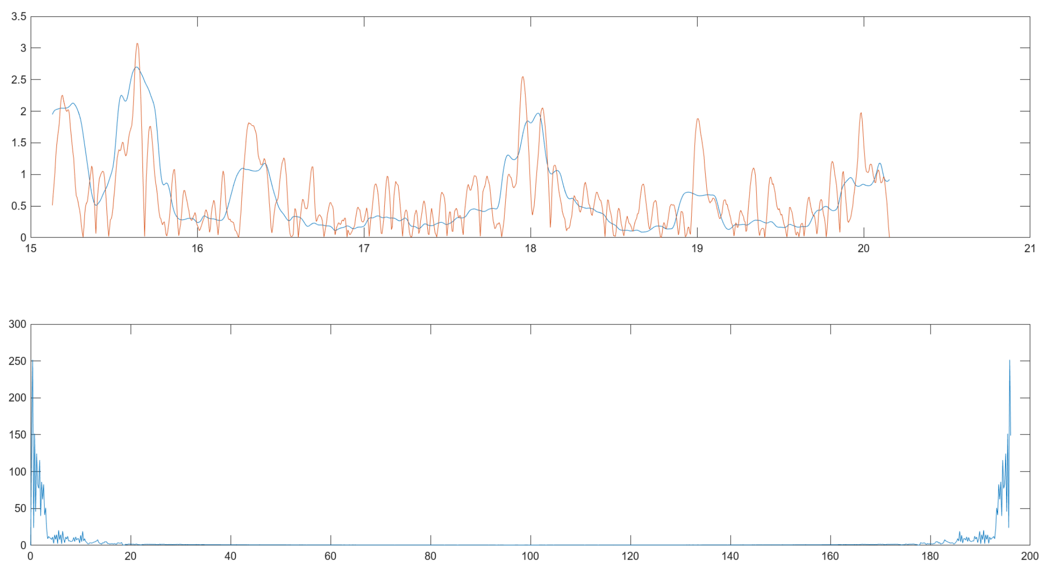

Figure 12: The Graph of Extracted Accelometer Data obtained from the Trajectort Estimation Example

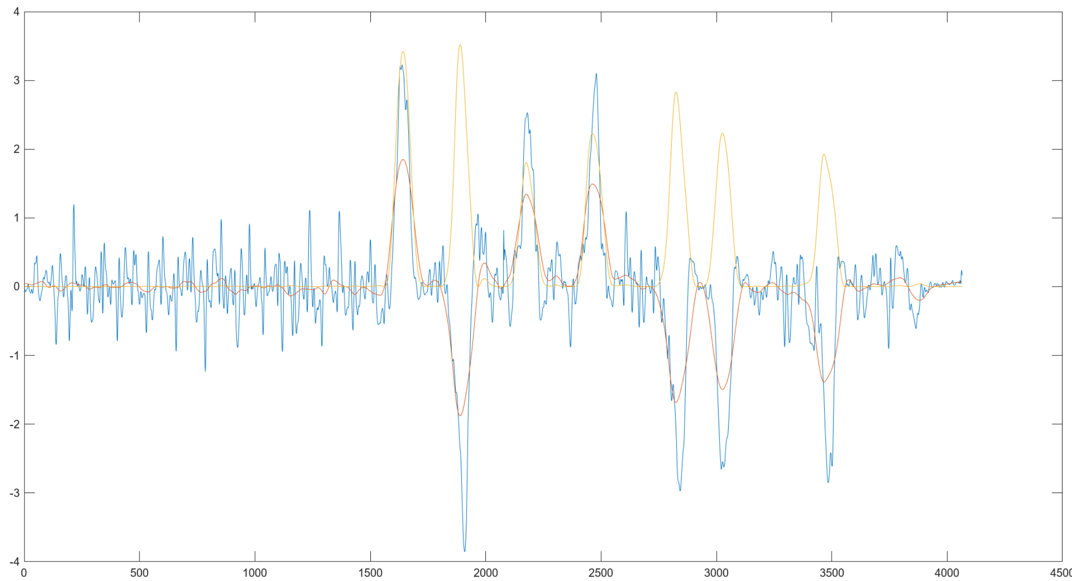

Figure 13: The Graph of Extracted Gyroscope Data obtained from the Trajectort Estimation Example

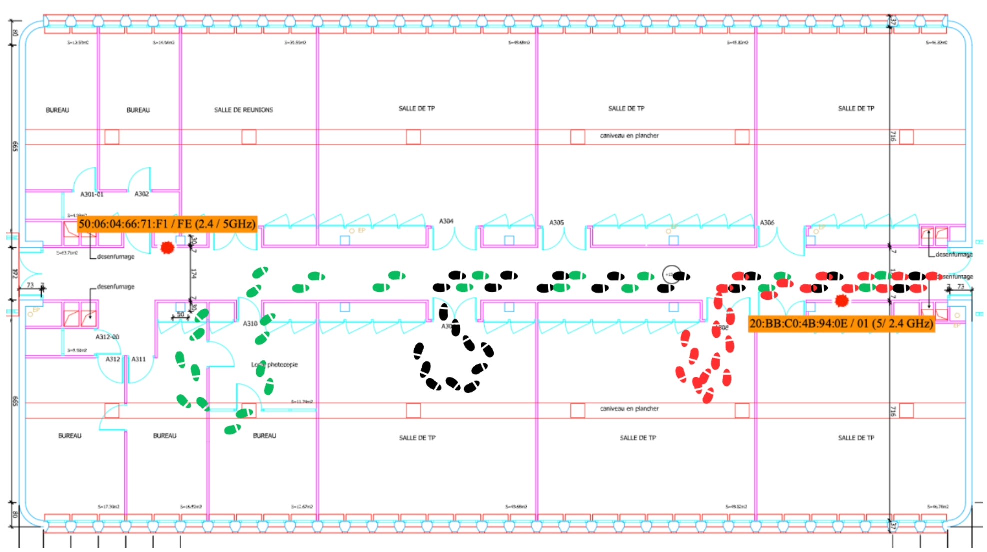

Figure 14: An Example of Other Trajectories can be obtain regarding the step size and speed of the person, green might represent the person with higher step size whereas red is for smaller step size

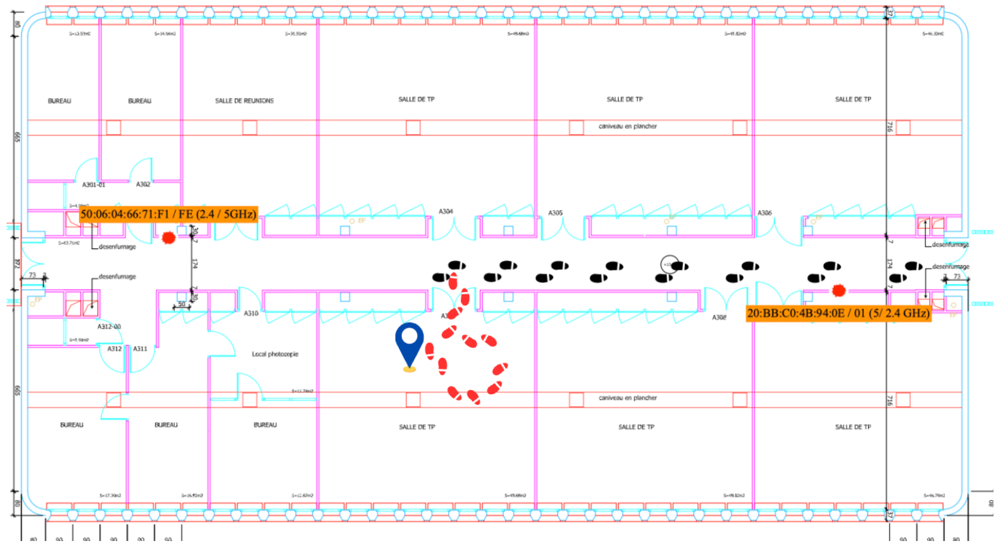

Figure 15: An Example of the Trajectory Estimation with 21 step untill the first turn (j) and total steps of 61 steps obtained from MATLAB Simulation

After founding succesfull trajectory estimation, the performance evaluation is made according to both the step counter errors calculated based on measurements and real-life counting and relative room likelihood error calculated based on the maximum likelihoods provided by the simulation itself.

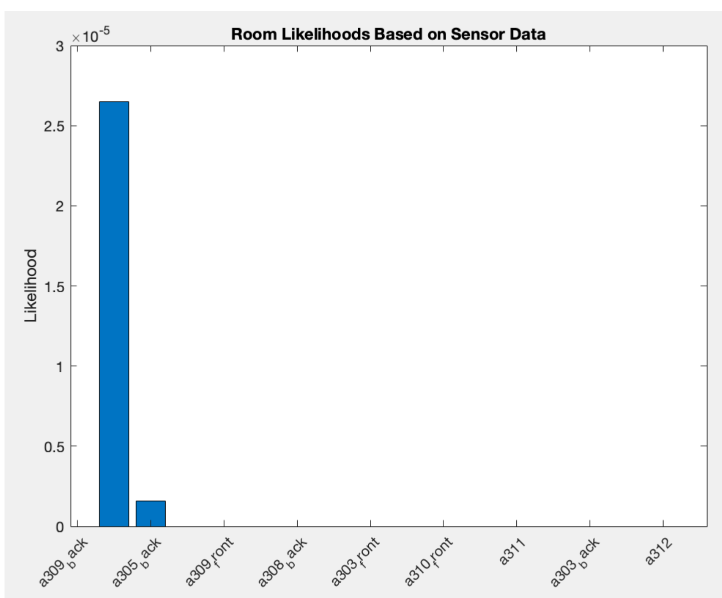

Figure 16: The Graph of the Room Likelihoods from RSS Simulation of the Trajectory Example

```
Columns 1 through 5

  {["a309_back"]}    {["a305_back"]}    {["a309_front"]}    {["a308_back"]}    {["a303_front"]}

Columns 6 through 11

  {["a310_front"]}    {["a311"]}    {["a303_back"]}    {["a312"]}    {["a307_front"]}    {["a305_front"]}

Columns 12 through 16

  {["a306_front"]}    {["a308_front"]}    {["a301"]}    {["a306_back"]}    {["a307_back"]}
```

Figure 17: The Classification of the Room Likelihoods from RSS Simulation of the Trajectory Example

By utilizing the room likelihood values calculated by the maximum likelihood estimation, the relative error probability is calculated as 6.02%.

$$Relative\ Error\ Probability\ (\%) = REP = \frac{1.59 \times 10^{-6}}{2.64 \times 10^{-5}} \times 100$$

$$REP = 6.02\%$$

V. Acknowledgements

Closed/ Open Door Adjustments:

We measured with and without closing the door to observe its effect. Closing the door increased variance by about 5 times and decreased the RSS. To ensure higher reliability, we took our data with the door open.

This choice was based on the need for more consistent and reliable measurements. Open-door conditions provided a more stable environment, minimizing fluctuations and ensuring the accuracy of our results (see Table 17). By controlling this variable, we aimed to enhance the reliability of our data, leading to more robust and credible findings. Thus, open-door measurements were preferred for our analysis.

ID of Access Point	Mean of RSS (Open Door)	Variance of RSS (Open Door)	Mean of RSS (Closed Door)	Variance of RSS (Closed Door)
251	-84.62	4.81	-84.11	18.30
351	-68.15	8.49	-76.16	7.25

Table 17: The Table of Open and Closed Door Measurement with A.P of 2nd Floor and 3rd Floor

VI. Conclusion and Recommendations

Indoor Positioning System using Sensor Fusion of Wi-Fi and Inertial Navigation System (INS) is successfully implemented. This approach is essential due to the inherent instability of Received Signal Strength (RSS) values, which change rapidly over time as illustrated in Table 1-16. The integration of INS helps to stabilize and improve the accuracy of the positioning system.

During testing, we evaluated the system's performance and identified specific error rates. The step counter error was recorded at 8.88%, derived from a test where an individual walked 45 steps in a corridor. Additionally, the room likelihood error was determined to be 6.02%, based on a specific trajectory example. These error rates provide valuable insights into the system's accuracy and effectiveness. By combining Wi-Fi RSS values with INS data, we significantly enhance the reliability and robustness of indoor positioning. This sensor fusion approach addresses the limitations of using Wi-Fi signals alone, offering a more stable and precise solution for indoor navigation and positioning applications.

To improve the Indoor Positioning System, it can be recommended that step counter can be adjusted to different variations according to user's speed and step size, as our current model assumes constant speed and step size for trajectory estimation. Additionally, enhancing gyroscope measurements by incorporating data from turns at various angles, rather than limiting observations to 90-degree turns, could provide a more comprehensive understanding of the gyroscope's performance. These adjustments will refine the accuracy of the system, making it more adaptable to real-world conditions where user movement is less predictable and more varied.

VII. Appendices

Appendix A - Pyhton Code for Extracting Mean and Variance of RSS values

```
import numpy as np
import os
import sys
np.set_printoptions(threshold=sys.maxsize)
textler= os.listdir("datalar")


def temizle(isim):
    a=open("datalar/"+isim,"r")

    ap=[np.array([])]
    mag=[np.array([])]
    for i in a:
        j = i.split(",")
        if (j[0]=='"eduroam"'):
            # print(j)
            j[1]=j[1].replace('"',"")
            j[2] = j[2].replace('"',"")
            ap=np.append(ap,j[1])
            mag=np.append(mag,int(j[2]))

    ap_names=[np.array([])]
    indexes=[np.array([0])]
    for i in range(len(ap)-1):
        if ap[(i)]!=ap[(i+1)]:
            indexes=np.append(indexes,i+1)
            ap_names=np.append(ap_names,ap[i])
    indexes=np.append(indexes,len(ap))
    ap_names=np.append(ap_names,ap[len(ap)-1])

    means=np.array([])
    vrs=np.array([])
    for i in range(len(indexes)-1):
        means=np.append(means, np.mean( mag[indexes[i]: indexes[i+1] ] ))
        vrs=np.append(vrs,np.var( mag[indexes[i]: indexes[i+1] ]) )

    vals=[ap_names, means, vrs]
    f = open("temizlenikler"+isim, "w")

    for i in range(len(ap_names)):
            f.write(ap_names[i]+"\t")
            f.write(str(means[i])+"\t")
            f.write(str(vrs[i])+"\n")

    f.close()
    return

for i in textler:
    temizle(i)
```

Appendix B - MATLAB code for Room Likelihood Estimation:

```
x = [-47; -63; -90; -91;-45; -79]; %test data

a301 = [
    351, -48.14, 7.66;   % FE
    352, -64.41, 4.79;   % OE
    251, -90.00, 0.01;   % DE
    322, -61.36, 11.86   % O1
    321, -46.68, 1.85;   % F1
    221, -81.28, 3.20    % D1
];

a303_back= [
    351, -52.37, 1.83;
    352, -62.73, 3.53;
    251, -83.77, 0.45;
    322, -71.57, 4.38;
    321, -58.03, 11.30;
    221, -76.11, 0.81
];
a303_front  = [
    351, -51.83, 4.81;
    352, -65.58, 4.74;
    251, -81.79, 2.91;
    322, -78.52, 12.67;
    321, -53.83, 15.06;
    221, -74.13, 22.11
];
a305_back = [
    351, -73.86, 5.15;
    352, -71.28, 1.58;
    251, -80.90, 1.20;
    322, -68.59, 3.48;
    321, -64.59, 8.31;
    221, -77.45, 20.52
];
a305_front= [    351, -57.95, 2.41;
    352, -54.41, 1.24;
    251, -75.86, 2.30;
    322, -58.29, 4.20;
    321, -58.59, 24.51;
    221, -70.36, 7.96
];
a306_front= [
    351, -57.29, 1.74;
    352, -51.94, 2.76;
    251, -86.42, 0.24;
    322, -45.00, 4.24;
    321, -56.88, 7.99;
    221, -79.59, 2.24
];
a306_back = [
    351, -61.39, 14.81;
    352, -57.29, 3.99;
    251, -93.00, 0.01;
    322, -56.79, 4.31;
    321, -66.46, 21.18;
    221, -87.05, 11.95
];
a307_front = [
    351, -63.41, 2.15;
```

```
    352, -57.82, 2.51;
    251, -86.59, 2.36;
    322, -48.95, 4.32;
    321, -61.77, 2.63;
    221, -82.95, 1.95
];
a307_back = [
    351, -77.48, 2.73;
    352, -66.84, 2.29;
    251, -88.0, 0.01;
    322, -67.24, 20.66;
    321, -73.92, 9.75;
    221, -91.12, 7.71
];
a308_back= [
    351, -81.72, 1.88;
    352, -67.28, 0.76;
    251, -84.68, 3.26;
    322, -67.88, 19.23;
    321, -75.44, 5.53;
    221, -74.4, 7.12
];
a308_front=[    351, -64.86, 5.91;
    352, -51.89, 0.67;
    251, -83.13, 0.46;
    322, -47.82, 3.00;
    321, -54.0, 4.86;
    221, -80.32, 15.36
];
a309_front = [
    351, -53.08, 17.99;
    352, -54.92, 20.30;
    251, -76.88, 4.79;
    322, -55.85, 12.21;
    321, -55.58, 13.24;
    221, -70.62, 6.16
];
a309_back= [
    351, -73.05, 1.13;
    352, -72.18, 3.06;
    251, -84.50, 1.70;
    322, -71.50, 3.34;
    321, -65.73, 1.93;
    221, -76.45, 9.98
];

a310_front= [
    351, -53.54, 3.94;
    352, -63.81, 5.08;
    251, -80.85, 5.98;
    322, -57.12, 8.49;
    321, -46.54, 8.33;
    221, -74.80, 15.00
];
a311= [
    351, -56.00, 3.30;
    352, -80.00, 2.10;
    251, -83.05, 5.45;
    322, -74.32, 5.37;
    321, -49.83, 6.03;
    221, -83.05, 5.45
```

```
];
a312 = [
    351, -54.88, 2.27;
    352, -80.56, 3.85;
    251, -84.96, 1.79;
    322, -63.50, 8.67;
    321, -50.24, 11.38;
    312, -84.96, 1.9
];

rooms = {a301, a303_back, a303_front, a305_back, a305_front, a306_front, a306_back,
a307_front, a307_back, a308_front, a308_back, a309_front, a309_back, a310_front, a311,
a312};
roomnames = {"a301", "a303_back", "a303_front", "a305_back", "a305_front",
"a306_front", "a306_back", "a307_front", "a307_back", "a308_front", "a308_back",
"a309_front", "a309_back", "a310_front", "a311", "a312"};

nrooms = length(rooms);

results = zeros(nrooms, 1);
for i = 1:nrooms
    testroom = rooms{i};
    results(i) = room_likelihood(testroom, x);
end


[sorted_results, sorted_indices] = sort(results, 'descend');


sorted_roomnames = roomnames(sorted_indices);


disp(sorted_roomnames);


figure;
bar(sorted_results);
set(gca, 'XTickLabel', sorted_roomnames);
xtickangle(45);
xlabel('Room Names');
ylabel('Likelihood');
title('Room Likelihoods Based on Sensor Data');

function p = room_likelihood(room, x)
    mu = room(:, 2);
    sigma = room(:, 3);
    sigma = diag(sigma);
    k = length(mu);
    p = (((2*pi)^(k/2)) * sqrt(det(sigma)))^(-1) * exp((-1/2) * (x - mu)' * (sigma^-1)
* (x - mu));
end
```

Appendix C - MATLAB Code for Step Counter via Accelometer:

```
clear
close all
acc_data=readtable("Acceleration with g 2024-06-12 10-41-48.xls");
acc=table2array(acc_data);
t=acc(:,1);
n=length(t);
t=acc(5:n,1);
x=acc(5:n,2);
y=acc(5:n,3);
z=acc(5:n,4);
mag=sqrt(x.^2 + y.^2 + z.^2);
n=length(t);

ts=0.0051;
fs=1/ts;

u1=mag-mean(mag);
u2=u1.^2;

k1=round(2*fs*1/8);
u=movmean(u2,k1);

wintime=5;

win=ceil(fs*wintime);
nwindows=ceil(length(u)/win);
nzeros=nwindows*win-n;


k2=round(2*fs*1/8);
% v=movmean(u,k2);

y=[u; zeros(nzeros,1)];
y=reshape(y,[win,length(y)/win]);

magm=[mag; zeros(nzeros,1)];
magm=reshape(magm,[win,length(magm)/win]);
t_append=t(length(t)):ts:t(length(t))+nzeros*ts;
tm=[t; t_append'];
tm=tm(1:length(tm)-1);
tm=reshape(tm,size(y));
n=length(y);
yw=(fft(y,[],1));

w=linspace(0,fs,win);


% figure
% subplot(2,1,1)
% plot(tm(:,5),abs(y(:,5)))
% subplot(2,1,2)
% plot(w,abs(yw(:,5)))
```

```
yw(1,:)=0;
peakfreqs=zeros(length(y(1,:)),1);

for i=1:length(y(1,:))
    %
    % figure
    % subplot(2,1,1)
    % plot(tm(:,i),abs(y(:,i)))
    % subplot(2,1,2)
    % plot(w,abs(yw(:,i)))
    yiw=abs(yw(:,i));
    yiw=yiw(1:ceil(length(yiw)/2));
    [pk,loc]= max(yiw);
    peakfreqs(i)=w(loc);

end
totalsteps=5*sum(peakfreqs);

q=4;
%
figure
subplot(2,1,1)
plot(tm(:,q),abs(y(:,q)))
hold on
plot(tm(:,q),abs(magm(:,q)-9.8))
subplot(2,1,2)
plot(w,abs(yw(:,q)))

% figure
% plot(t,u)
```

Appendix D - MATLAB Code for Turn Counter with Direction via Gyroscope:

```
clear
close all

j=1i;

gyrdata=readtable("Gyroscope rotation rate 2024-06-12 10-41-45.xls");
gyr=table2array(gyrdata);
ts=0.009977;
fs=1/ts;

tgyr=gyr(:,1);
n=length(tgyr);
tgyr=gyr(5:n,1);
xgyr=gyr(5:n,2);
ygyr=gyr(5:n,3);
zgyr=gyr(5:n,4);
maggyr=sqrt(xgyr.^2 + ygyr.^2 + zgyr.^2);

k1=round(fs*1);
u=movmean(zgyr,k1);
k2=round(fs*1/4);
v=movmean(u,k2);
w=v.^2;
vavg=sum(w)/length(w);
[peask, locs]=findpeaks(w,"MinPeakHeight",vavg);
turns=zeros(length(locs),1);
turntimes=zeros(length(locs),1);
for i=1:length(locs)
    turns(i)=j*sign(v(locs(i)));
    turntimes(i)=tgyr(locs(i));
end

plot(zgyr)
hold on
plot(v)
hold on
plot(w)
```