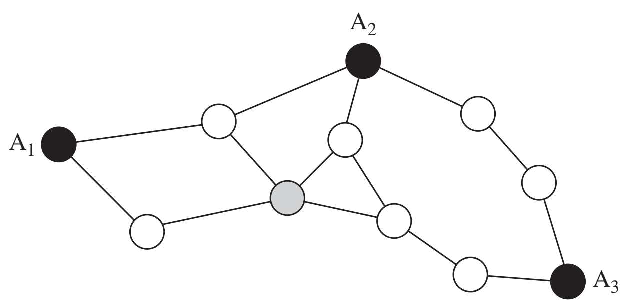
Department of Electrical and Computer Engineering
University of Waterloo
ECE-493-659 IOT and Intelligent Sensors and Sensor Networks
Assignment 3: Due Date (July 25th)-11:59PM

Question 1 [10 pts]:

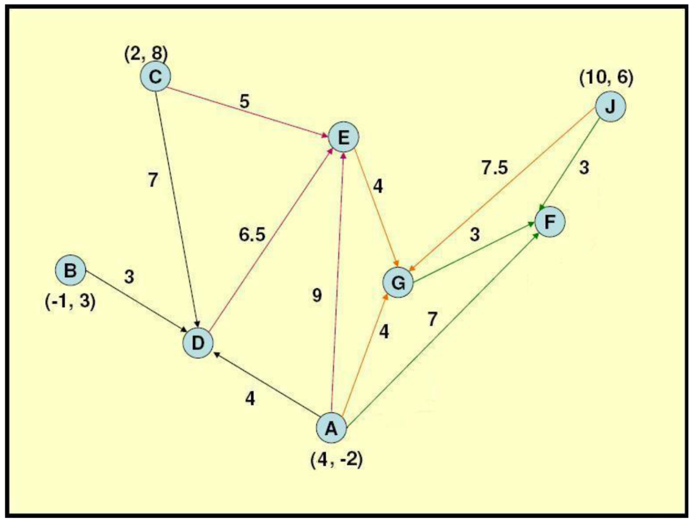
The figure below shows a network topology with three anchor nodes. The distances between anchors A_1 and A_2, anchors A_1 and A_3, and anchors A_2 and A_3 are 40 m, 110 m, and 35 m, respectively. Use the Ad Hoc Positioning System to estimate the location of the gray sensor node (show each step of your process).



Question 2 [10 pts]:

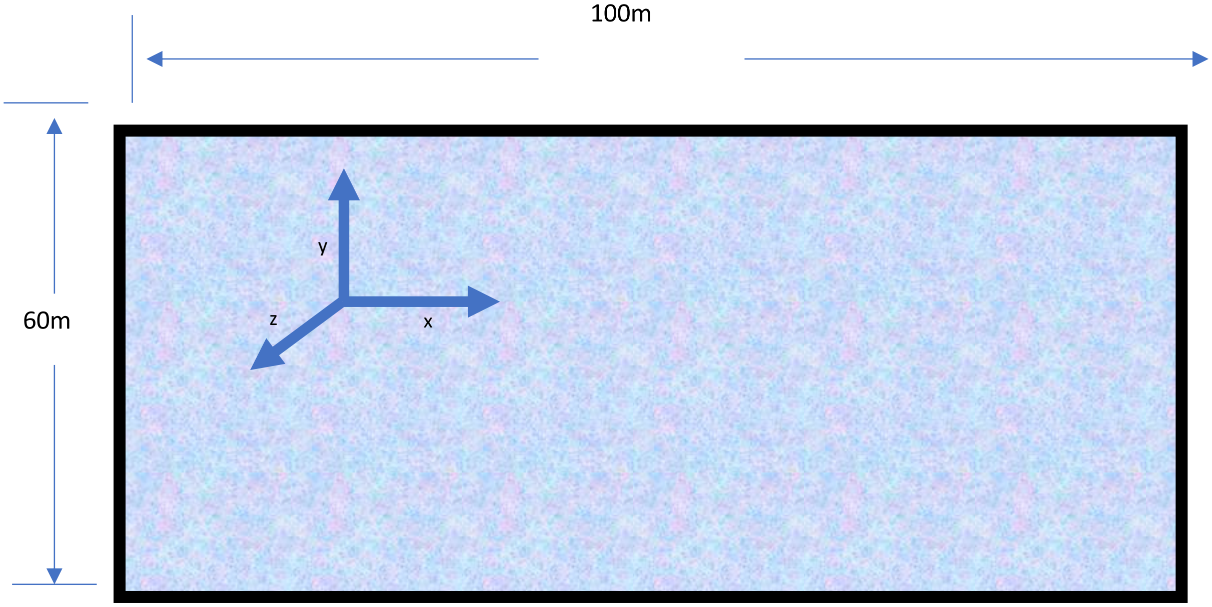
For the IoT network given in the figure below,

- Find out the location of each node based on multilateration with the information of anchor node coordinates and the distance between nodes given in the figure.
- Show how the DV-HOP ad-hoc positioning technique can be used to estimate the location of each node



Question 3 [15 pts]:

Consider the case of the interior of a building of a rectangular shape 100mx60mx5m.



It is desired that objects moving around inside this building be located by means of the wireless signals propagating inside the building. These signal are produced by three wireless devices: one device is located at (x=0.0m,y=30.0,z=3.0m), one device is located at (x=50.0m, y=60.0m, z=4.0m), one device is located at (x=100.0 m,y=30.0m,z=3.0m). The floor of the building is a grid of equal size square-tiles. It suffices to locate the device roaming inside the building in terms of a tile index.

RSSI Model: Please refer to the article "Indoor Positioning Algorithm Based on the Improved RSSI Distance Model", posted on the course site.

Common propagation path-loss models include the free space propagation model, the logarithmic distance path-loss model, etc. Studies have shown that the channel fading characteristic follows a lognormal distribution. RSSI distance measurement generally uses the logarithmic distance path-loss model [32–34]. It is expressed as

$$RSSI = -10n\lg\left(\frac{d}{d_0}\right) + A + X_\sigma, \tag{1}$$

where d is the distance between the transmitter and the receiver, and n is a path-loss parameter related to the specific wireless transmission environment. The more obstacles there are, the larger n will be. A is the RSSI with distance d_0 from the transmitter. X_σ is a Gaussian-distribution random variable with mean 0 and variance σ^2.

For convenience of calculation, d_0 usually takes a value of 1 meter. Since X_σ has a mean of 0, the distance-loss model can be obtained with

$$\overline{RSSI} = -10n\log(d) + \overline{A}, \tag{2}$$

where $\overline{A}$ is the average measured RSSI when the received node is 1 meter away from the transmit node which is related to the RF circuits of Bluetooth nodes. By gathering the RSSI values for Bluetooth beacons at different distances and using the least squares algorithm to fit the parameters, we can obtain the RSSI distance model.

Assuming the average measured RSSI at one meter away from the transmitter to be -50dbm; the average path-loss to be 4dB; and a standard deviation of 5.1dB.

1. Using the model in Equation 2, generate an RSSI profile as a function of the distance d, for d=1 to 140m.
2. Generate the fingerprint for the tile grid. Each grid tile fingerprint is the RSSI readings from the three devices measured at that particular tile. Use the center of the tile for your calculations.
3. Consider a roaming device, placed at the centre of tile indexed by (30 on the x-dimension, 45 on the y-dimension,0 on the z-dimension). Estimate the RSSI readings using the same model.
4. Compute the tile location of the roaming device by matching its RSSI readings as in 3 above, with that stored in the grid fingerprint. Repeat this ten times and compute the mean location value.
5. Compute the location error, i,e, the distance between the true tile location and the mean location value.
6. Using the estimated reading in 3 above and the RSSI model, compute the distance between the roaming device and each wireless anchor. Use a triangulation technique to estimate the three dimensional location of the roaming device. Compare that to true location.

Question 4 [10 pts]:

Suppose we have two sensors with known (and different) variances v_x and v_y, but unknown (and the same) mean μ. Suppose we observe n_x observations from the first sensor and n_y observations from the second sensor. Call these $\mathcal{D}_x$ and $\mathcal{D}_y$. Assume all distributions are Gaussian.

1. What is the posterior $p(\mu|\mathcal{D}_x, \mathcal{D}_y)$, assuming a non-informative prior for μ? Give an explicit expression for the posterior mean and variance. Hint: use Bayesian updating twice, once to get from $p(\mu) \rightarrow p(\mu|\mathcal{D}_x)$ (starting from a non-informative prior, which we can simulate using a precision of 0), and then again to get from $p(\mu|\mathcal{D}_x) \rightarrow p(\mu|\mathcal{D}_x, \mathcal{D}_y)$.
2. Suppose the y sensor is very unreliable. What will happen to the posterior mean estimate? Give a simplified approximate expression.

Question 5 [10 pts]:

Given that the sensors provide the following assessment in the form of mass functions as in the table below, use DS evidence fusion to compute the evidence on each potential identity. Calculate the conflict factor.

Identity	Sensor D_1	Sensor D_2
F	0.3	0.4
M	0.15	0.10
A	0.03	0.02
Animal	0.42	0.45
Unknown	0.10.	0.03
Total Mass	1.00	1.00

Question 6 [10 pts]:

Compressed Sensing:

a) Create a sparse vector of 512 random sensory values. Plot this vector
b) Create a random measurement matrix to compress the sensory vector in a) to a compressed version consisting of 128 values. Plot this vector.
c) Use the Matlab function l1eq_pd function to recover the 512 sensory data. Plot the recovered signal and compare to the original one in (a) by computing the correlation factor between the two signals).