Implementation of Kalman Filter Method in COVID-19 Patients Monitoring Application based on Bluetooth Low Energy (BLE)

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Abstract: The COVID-19 disease is currently declared to be a global pandemic. Self-quarantining at home is one of the best solutions proposed to prevent COVID-19 spread and patient monitoring system will be useful for tracking the patient's position during the implementation of this self-quarantine. The purpose of this paper is to implement the Kalman Filter method to processing RSSI value from BLE beacons in order to obtain distance values that resemble the real distance, so it can be used in the COVID-19 patient monitoring application. The distance will be calculated using the Log Normal Shadowing method and the estimation process will use the Kalman Filter method to obtain the distance value that is resemble to the real distance. From the test results, it show that the Kalman Filter method provides a distance value that resemble the actual distance with an error of 8.7%. While the Kalman Filter method is implemented in the patient monitoring application, it successfully sends the warning notification with success rate of 94% for patient and 90% for admin. The results show that the Kalman Filter method is appropriate to be implemented in the COVID-19 patient monitoring application.

1 INTRODUCTION

Coronavirus (COVID-19) is a highly contagious disease that hit the world in early 2019. This disease is caused by the SARS-CoV-2 virus (Kementrian Kesehatan RI, 2020) and was first identified in Wuhan, the capital of China's Hubei province and since then COVID-19 has been spread globally and become a pandemic according to the statement of the World Health Organization (WHO) (Hui, et al., 2020). Based on research, it shows that the speed of transmission of COVID-19 is fast, so preventive measures are needed. Therefore on February 29 2020, the Indonesian Government released a disaster emergency status and promoted social distancing and self-quarantine movements to break the chain of transmission (Buana, 2020).

Regulations regarding self-quarantine are regulated in UU no. 6 of 2018 about Health Quarantine and there are several kinds of arrangements regarding quarantine, one of them is about home quarantine (Sanur, 2020). Home quarantine means that a person is not allowed to leave the house to do self-isolation. The person in the category of People Under Monitoring (ODP) or Patients Under Monitoring (PDP) must quarantine at home. This quarantine strategy has been used by the Chinese government previously by requiring people to stay at home and the Chinese people also support this policy considering the previous SARS incident, so the pandemic becomes more controlled (Guo, et al., 2020).

Currently, the self-quarantine process is carried out by COVID-19 patients based on the awareness of the patients themselves without any supervision. Therefore, to make self-quarantine activities successful and make the self-quarantine process more controlled, a monitoring system needs to be implemented for every patient who is currently doing self-quarantine in their home.

In a previous study about the Alzheimer's patient monitoring system using BLE (Bluetooth Low Energy) (Pratiarso, et al., 2018), the calculation of the patient's position was using the Log Normal

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Shadowing method. By considering the power of the signal sent by the BLE beacon and received by the Raspberry Pi device as a function of distance in increments of several grades. Distance data will be processed using the Kalman Filter method as a noise filter that can reduce positioning accuracy. When the patient's distance is less than 10 meters, there will be a warning notification on the nurse application. Another similar application is the research about mapping visitors to the Trowulan Museum with the purpose of mapping the position of visitors using BLE (Anggita, et al., 2019).

The weakness of previous research is the use of BLE beacon and Raspberry Pi that is less user friendly, compatible, and more expensive because BLE beacon and Raspberry Pi devices are needed. While in this study, BLE beacon and smartphone applications will be used so it will be cheaper and easier to implement because almost everyone has smartphone.

The purpose of this paper is to implement the Kalman Filter method to processing RSSI value from BLE beacons in order to obtain distance values that resemble the real distance, so it can be used in the COVID-19 patient monitoring application. This BLE beacon has the advantages of being cheap, lightweight, and does not require external power. The monitoring application will calculate the distance from the BLE beacon using the received signal strength (RSSI) and estimate data with the Kalman Filter method. The estimated distance data obtained using the Kalman Filter method is used to run a warning notification system that will send a warning notification to the patient's and admin's smartphones at the specified distance limit.

2 TRACKING METHOD AND DATA ESTIMATION

2.1 Position Tracking Method

The position tracking method using RSSI values has been widely used today. To obtain the distance value from RSSI, the value must be converted using the Log Normal Shadowing method. The Friis free space model was used to build the Log Normal Shadowing method for predicting the presence of severe signal interference produced by propagation attenuation in an environmental area. This also demonstrates the irregularity of the RSSI value (Pratiarso, et al., 2017).

The Log Normal Shadowing equation is needed because the attenuation of electromagnetic wave propagation between transmitter and receiver might impact the signal strength value in a wireless communication system. The transmission signal strength generated by the transmitter and received by the receiver at a reference distance (1 meter) is assumed to be *PRX0* in the Log Normal Shadowing equation (1), and the received signal strength at a given distance is *PRX*, where there is an additional signal propagation attenuation expressed in *Xσ* as a gaussian random distribution variable with zero mean and standard deviation *σ*.

$$-P_{RX} = -P_{RX0} + 10n \, log \frac{d}{d0} + X_{\sigma} \qquad (1)$$

The path loss coefficient in equation (2) for the observation area is obtained from equation (1).

$$n = \frac{P_{RX0} - P_{RX}}{10log^{d}/_{d0}} - X_{\sigma} \qquad (2)$$

The distance computation based on the detected signal strength is d, while *d0* is a fixed reference distance of 1 meter. Table 1 shows the variations in the value of the path loss coefficient *n* in various observation areas.

Table 1: Variations in Path Loss Coefficient Values.

Environment	*n*
Free Space	2
Urban Area	2.7-3.5
Inside Building (LOS)	1.6-1.8
Inside Building (NLOS)	4-6
In a Factory (NLOS)	2-3

The estimated distance *d* using equation (3) between the transmitter and the receiver is calculated after the path loss coefficient value is obtained from the observation area. It's important to note that the value of *n* only applies to the location where the RSSI data observation/measurement took place at the moment. A new path loss coefficient value is required if the RSSI is measured in a different location area.

$$d = d_0 10^{\frac{P_{RX0} - P_{RX}}{10n}} \qquad (3)$$

2.2 Kalman Filter Data Estimation Method

The same problem that IPS (Indoor Positioning System) devices face all the time is an unstable signal caused by noise inside the room, which results in inaccurate measurement data, so it requires the use of an estimating method such as Kalman Filter.

The Kalman Filter method is a set of mathematical equations for predicting values using feedback control form in such a way that minimizes the average of mean squared error (Gunjal, et al., 2018). This method is commonly used to estimate the real state using earlier data that contains noise and other unreliable elements. This method performs in two stages, one of which is prediction and the other is correction (Mackey, et al., 2018). Both of these procedures run continuously until a time limit is reached.
Prediction Stage:

$$x_{k+1} = A_k x_k + B_k U_K \tag{4}$$

$$P_{k+1} = A_k P_k A_k^T + Q_k \tag{5}$$

We will look for distance data X_{k+1} in the first stage of prediction as in (4), which are the results of the estimate distance to the next value based on the long of *k* value (time) or the outcomes of the previous correction stage. Then the error covariance P_{k+1} is calculated in (5), where the result of this error covariance estimation value is also obtained from the previous correction stage added with noise covariance variabel Q_k. This Q_k variable has been determined at the beginning and is obtained through measurement experiments.
Correction Stage:

$$S_k = H_k P_k H_k^T + R_k \tag{6}$$

$$K_k = P_k H_k^T S_k^{-1} \tag{7}$$

Measurement update

$$x_{k+1} = x_k + K_k(y_k - H_k x_k) \tag{8}$$

$$P_{k+1} = (1 - K_k H_k) P_k \tag{9}$$

The kalman gain value (K_k), which is the relative weight of the state is searched in the correction stage and applied as a multiplier coefficient for the next estimation result. S_k is measurement covariance to obtain the value of the kalman gain (K_k). In addition to Q_k there is a variable R_k, which is the covariance of observational noise. The R_k variable's value is determined at the begin and obtained through experiments. Then update the next estimated value based on the current value y_k. After updating the estimate data, the error covariance of the new estimated value is also updated. For the next prediction step with new *k*, the new X_k and P_k values will be applied.

3 PROPOSED TRACKING SYSTEM

As illustrated in the system block diagram in Figure 1, a system design was applied to monitor the patient's position based on the patient's distance from BLE in this research. Patients who are doing self-quarantine at home will bring an Android smartphone as a receiving device, according to the system design. This Android smartphone will come with a monitoring application that will catch the bluetooth signal from the BLE installed at the exit door. The signal strength data called RSSI, will be obtained from the signal received by the monitoring application and forwarded to the server to be converted into distance data.

On this server, the conversion is performed using the Log Normal Shadowing method, then followed by distance estimation using the Kalman Filter method to produce more precise distance data. The estimated distance data obtained using the Kalman Filter method is used to run the server that will send a warning notification to the patient's and admin's smartphones if the patient is detected approaching the exit door (within 2 meters).

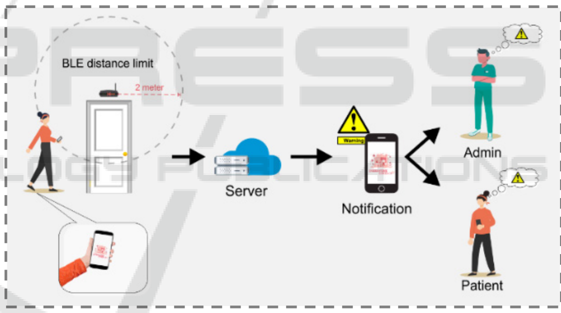

Figure 1: Block Diagram of the System.

3.1 Experimental Setup

The BLE beacon will be placed above the door at a height of 2 meters from the floor in this experimental scenario. The BLE beacon was placed above the door since it is the most strategic and provides LOS conditions (Line of Sight), that is direct communication between the BLE beacon (transmitter) and smartphone (receiver) with no obstacles. The HM-10 BLE module is the type of BLE device utilized in this research, as illustrated in Figure 2, with specifications shown in Table 2.

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Table 2: Specifications of BLE HM-10.

Specifications	Notation
Protocol	V4.0 BLE
Supply Voltage	2-3.7 Volt
Size (mm)	26.9 x13 x 2.2
Data rate	256 Kb
Battery	CR2032

Figure 2: HM-10 BLE Module.

The observation room is a 4 × 3.3 meters area with LOS conditions (Line of Sight) in Figure 3. BLE acts as a transmitter, broadcasting the signal at any particular time. Then the patient's smartphone as receiver will receive this signal at 28 different measurement points in the form of RSSI data in decibels (dBm). These 28 points are labeled as A1 to D7 and have varying distances to evaluate distance conversion accuracy all around the observation room. This RSSI data is used to calculate distance using the Log Normal Shadowing method, with the P_{RX} value as the result.

In addition to measuring RSSI data (P_{RX}) that will be turned into distance as in equation (3), it is also important to measure RSSI data at a defined distance such as 1 meter. Figure 4 illustrate the P_{RX0} measurement scenario.

Figure 3: Scenario of RSSI Data Measurement Location.

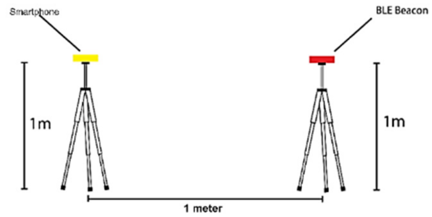

Figure 4: Illustration of P_{RX0} Measurement.

3.2 Design of the Kalman Filter Method

Kalman Filter method in this system helps to estimate distance data in order to obtain more precise distance estimates. Considering that this algorithm implements the feedback control principle, the processes that occur will be related and have an impact to each other. It is important to initialize the initial value before using the Kalman Filter method. The variable values in the Kalman Filter system are defined as follows based on the flowchart in Figure 5.

Because the filter will converge by trusting the value of x_0 from the start, the amount of kalman gain, cannot be set to 0. Meanwhile, the values of Q (process noise covariance) and R (measurement noise covariance) remain constant, at 1×10^{-3} and 100. The distance data will be predicted and a temporary status will be obtained using the distance data values collected earlier in the prediction stage.

The kalman gain value is calculated using the estimated covariance error P_k and the measurement noise covariance P, which is constant at 100. Calculate the covariance of the new estimation error P_k, which will be applied in the next state correction process in addition to the estimated distance x_{k+1}. Check the number of distance data as n and repeat the state prediction process, meanwhile if k equals n the loop ends and a new state x value is created as a result of the estimation.

4 EVALUATION AND EXPERIMENTAL RESULT

4.1 Measurement of Path Loss Index (n)

Measurement of path loss index (n) using the Log Normal Shadowing equation and the RSSI value obtained from the results of the RSSI data measurement scenario, namely the RSSI value (P_{RX}), the RSSI value at a distance of 1 meter (P_{RX0}) and the Gaussian Normal Distribution value ($X\sigma$). From the calculation of the path loss coefficient (n) obtained using (2) is shown in table 3 with the value of n is 1.4 and RSSI or Tx power is -80.05 dBm.

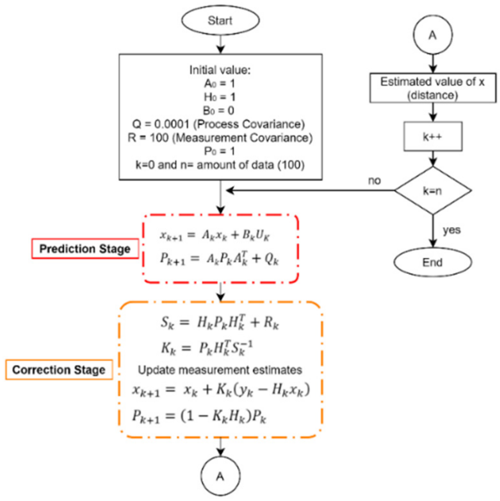

Figure 5: Kalman Filter Flowchart.

Table 3: Path Loss Coefficient Average Value.

Position	RSSI (dBm)	Path Loss Coefficient (n)
A1	-81,09	2,95
A2	-79,92	3,33
A3	-75,63	1,11
A4	-75,23	0,87
A5	-75,51	0,9
A6	-77,2	1,6
A7	-76,59	0,65
B1	-81,21	1,84
B2	-78,58	1,23
B3	-80,27	1,96
B4	-76,65	0,63
B5	-78,14	0,6
B6	-79,32	1,5
B7	-80,31	1,47
C1	-84,14	1,98
C2	-80,27	0,97
C3	-79,92	1
C4	-82,98	1,95
C5	-77,88	0,56
C6	-79,63	0,94
C7	-79,16	0,83
D1	-84,81	1,59
D2	-83,92	1,63
D3	-83,95	1,65
D4	-84,12	1,36
D5	-80,66	0,95
D6	-80,15	0,93
D7	-84,06	1,57
Average n		1,4

The distance calculated using equation (3) and the path loss coefficient value (n) of 1.4 to convert the received RSSI value from the measurement at 28 different points resulting the distance shown in Figure 6. The largest gap in calculated distance occurs at point C5, with a 47.5% estimation error, while the closest estimate to the actual distance occurs at point B3, with 12% estimation error.

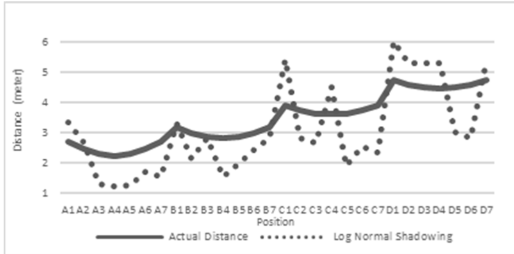

Figure 6: Comparison of actual distance and calculated distance of Log Normal Shadowing.

However, the average estimation error obtained by the Log Normal Shadowing method is still larger than the allowable standard error of 30.3%, making the estimation results less reliable.

4.2 Kalman Filter Distance Estimation Results

The Kalman Filter method is used to perform the distance estimation process in two stages: prediction and correction. As displayed in Figure 7, the estimation of the patient's position is more accurate as a result of the estimation process. Figure 8 illustrates the decrease in the percentage of error while calculating the distance using only the Log Distance method and after going through the Kalman Filter method.

The largest estimation gap still occurs at the C5 position, but with a much smaller estimation error of 14.2%, and the smallest estimation error in B3 is just 1.3%. So based on the results, the Kalman Filter method can provide an accurate distance estimate with an average error of 8.75%, which is acceptable because it is less than the permitted standard error of 10%.

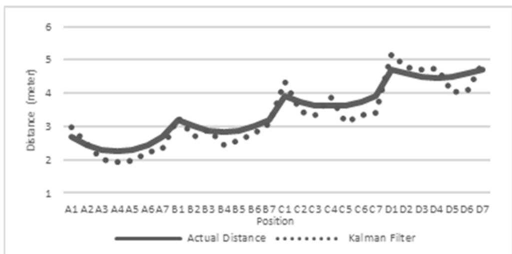

Figure 7: Comparison of the actual distance and the estimated distance of Kalman filter.

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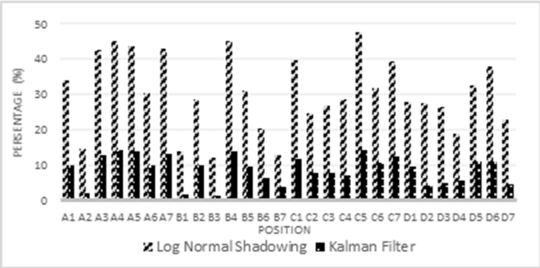

Figure 8: Comparison of the percentage error of Log Normal Shadowing and Kalman Filter.

4.3 Application Monitoring

The results of distance calculation using Log Normal Shadowing method with path loss coefficient (n) of 1.4 is resulting an error of 30.3%. After distance calculation using Log Normal Shadowing method, this distance data is estimated using Kalman Filter method so the error decreases to 8.75% and the distance data becomes more similar to the actual distance value. This Kalman Filter method is implemented in the COVID-19 patient monitoring application based on the results of this distance calculation to generate more accurate warning notification system. Warning notification system will send a notification to the monitoring application when the patient is less than 2 meters away from BLE. Figure 9 shows an example of a notification display.

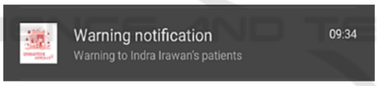

Figure 9: Display of Warning Notification.

A test was conducted using a smartphone and a BLE beacon at a distance of 2 meters to evaluate the performance of warning notification system, as shown in Figure 10. According to the results of the tests as shown in Figure 11 with a total of 50 tests, the patient's smartphone received notifications 47 times with success rate of 94%. While the admin's smartphone received notifications 45 times with success rate of 90%. These results show that this warning notification system is accurate and reliable because affected by precise distance calculations.

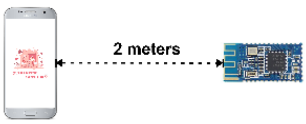

Figure 10: Notification Test Scenario.

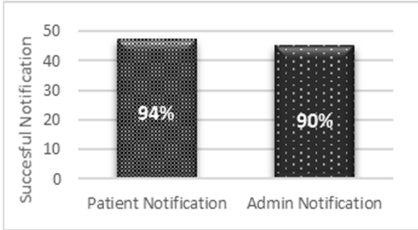

Figure 11: Graph of Notification Success Percentage.

5 CONCLUSIONS

In this paper, a system is proposed to implement the Kalman Filter method to processing RSSI value from BLE beacons in order to obtain distance values that resemble the real distance, so it can be used in the COVID-19 patient monitoring application.

Several results have been obtained from this study, including distance calculation using the Log Normal Shadowing method with path loss coefficient (n) of 1.4 is not accurate enough because the average error is quite large, that is 30.3%. Distance calculation using Kalman Filter method can increase the accuracy from 30.3% without Kalman Filter method to 8.75% with Kalman Filter method, which is less than the allowable standard error estimate of 10% (Pratiarso, et al., 2018). The success rate of the warning notification system in monitoring application to sending notifications is 94% for patient and 90% for admin.

Based on these results, the Kalman Filter method is appropriate to use in the data estimation process in monitoring application because it can improve the accuracy of distance calculations and the success rate of the warning notification system.

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