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Method for RSSI Heat Map Estimation using Radial Basis Functions for Fingerprinting Localization

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ABSTRACT

Radio Frequency (RF) based indoor localization is a challenging task due to the dynamic and multipath factors although many research proposed different improvement strategies in their indoor localization works. This paper discusses an alternative method for RF-based mapping estimation for Received Signal Strength Indicator (RSSI) fingerprinting indoor localization. The RSSI fingerprinting mappings are estimated by different Radial Basis Function (RBF) interpolation methods. The RBF interpolation methods may reduce the number of fingerprint locations required for fingerprinting localization. The predicted RSSI and actual RSSI radio mappings are compared to determine the accuracy of each RBF. The best mean error of 2.008dBm in Inverse Multiquadric RBF is achieved between the actual and predicted mappings in a complex laboratory environment. The RF-based mapping estimation techniques presented in this paper have shown that the effectiveness to fulfil the perquisite of fingerprinting localization with lower time and labour requirement.

Keywords: Fingerprinting Localization, Radial Basis Functions, Received Signal Strength Indicator

1. INTRODUCTION

One of the most promising methods in RF-based indoor localization in terms of performance is RSSI fingerprinting localization. The advantages of RSSI fingerprinting localization method are its high adaptability among Wireless Sensor Network (WSN) devices and it avoids additional hardware to support the localization [1,2]. Most RSSI fingerprinting localization works offer high accuracies in location determination but suffer from labour intensive and time requirement to build up the fingerprinting database [3,4]. Generally, the RSSI fingerprinting localization method is divided into two stages: Offline and online stages. During the offline stage, the researchers are required to perform site survey within the indoor environment by collecting the RSSI values on each of the fingerprint locations [5]. It is a labour-intensive process for site surveying a large indoor environment. All the collected RSSI data that represent the fingerprint locations are saved into a database for the online stage. During the online stage, the location of devices is determined by matching the received RSSI transmitted by the device with the location with the least dissimilarity available in the database. However, the pre-saved RSSI database is susceptible to degradation due to changes in the environment. Due to the degradation factors, the RSSI radio maps are required to be recalibrated after some time elapsed or any physical changes within the environment [6]. This results in additional time and labour required to maintain the quality of RSSI fingerprinting radio maps for localization.

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To reduce the time and labour required in fingerprinting localization, this paper proposes an alternative method to estimate the RSSI radio maps with RBF interpolation methods. This paper suggests the estimation of RBF interpolated RSSI radio maps with probabilistic approach could reduce the number of fingerprint locations for RSSI fingerprinting localization.

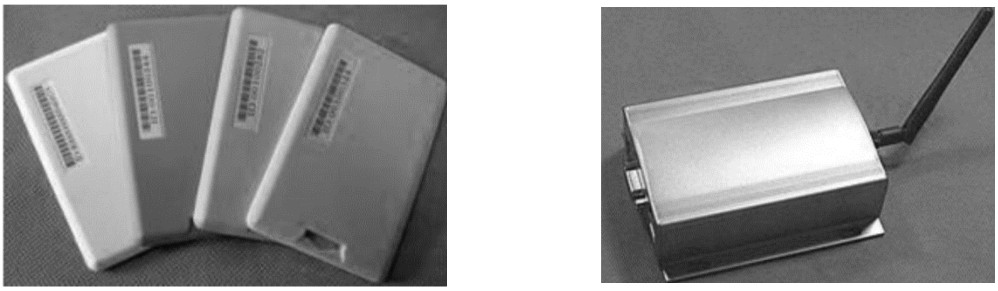
Despite the high popularity in RSSI fingerprinting localization, many works suggested that the fluctuating characteristic of RF signal propagation within the indoor environment may degrade the overall localization performance [7,8]. As the formation of radio maps may not be accurately representing the fingerprint locations due to this characteristic of RSSI. In order to reduce the impact of variation in RSSI, [9] studied the nature of signals in indoor propagation to ensure the reliability of signal transmission within the environment. However, the signal propagation for indoor environment could be affected by many factors such as unique environment size, multipath effect, presence of obstacles such as human or objects and temperature and humidity inside the environment [10-12]. Furthermore, the RSSI data collected within the environment are subjected to packet losses during the transmission among WSNs [13]. Due to the factors, it is a time-consuming and laborious effort to maintain the RSSI radio maps for fingerprinting localization.

Recent works have proposed various interpolation methods among fingerprint locations to reduce the efforts required for the development of RSSI radio maps [14-17]. For instance, the Kriging interpolation method has been presented in [15] for time-variant multi-phase RSSI radio maps. In this work, the authors suggested the performance of fingerprinting localization can be improved by considering different RSSI radio maps at different time periods. It was mentioned that RSSI radio maps might have shortcomings of inaccessible locations and unknown distances separation between WSN devices in practical. Therefore, the Kriging interpolation method was proposed to estimate the RSSI radio maps for the region of interest. However, the discussions suggested that RSSI radio maps estimated by Kriging interpolation are affected by the placement of WSN devices and human presence within the environment. Higher positioning errors were observed in both single-phase and multi-phase validations when activities were performed within the environment. Another work in [17] reported that Kriging interpolation method outperforms its competitors in location estimation but it is still susceptible to the ambiguity of the collected signal data for location estimation.

The radio map interpolation methods proposed from previous works are commonly affected by the physical condition and activities within the indoor environment. Therefore, this paper proposes an alternative approach to estimate the RSSI radio maps for fingerprinting localization. The RSSI radio maps are estimated with different RBF interpolation methods. With the consideration of the probabilities of RSSI in each fingerprinting location, the RBF interpolated probabilistic radio mappings are obtained. Different types of RBF interpolation methods were used to compare their probabilistic estimations for RSSI fingerprinting localization. The performance of RBF interpolated RSSI mappings are determined based on the comparison between the interpolated prediction and the conventional RSSI fingerprinting mappings formation.

2. MATERIAL AND METHODS

The experiments in this work are performed with a 2.45GHz active Radio Frequency Identification (RFID) system (OmniDirectional Reader F3411 and UHF Tag T3433) with 15dBi omnidirectional receiver antenna. The 2.45GHz active RFID system that includes the RFID tags and receivers for this experiment are shown in Figure 1.



(a) (b)

Figure 1. 2.4GHz RFID hardware used (a) RFID tags (b) RFID receivers

The experiment platform is performed in one of the Universiti Malaysia Perlis (UniMAP) laboratories which has the size of 24m × 8m as shown in Figure 2. There are four identical RFID receivers placed in different locations to collect RSSI values in each fingerprint location. The RFID receivers are mounted on the walls at a fixed height of 1.4m from the ground.

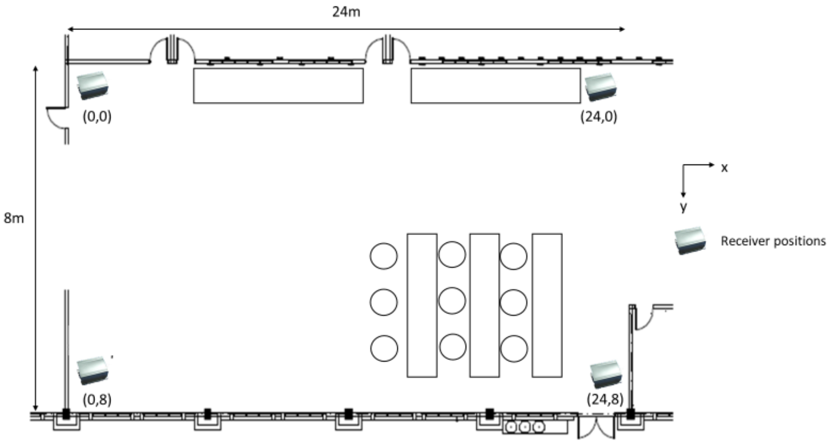


Figure 2. Experimental laboratory testbed size of 24m × 8m with receivers' placement locations

There are a total number of 225 fingerprint locations with 1m×1m grid separation within the experimental environment. However, there are only 197 accessible fingerprint locations in the laboratory environment to collect the RSSI values due to obstruction by furniture placement and laboratory structure. Similar to the traditional fingerprinting localization method, each available fingerprint location has its RSSI values collected for a certain number of samples. In this work, the RSSI values are collected for one-minute with a sampling rate of 1Hz. Assume that $f_{(x,y),n} = \{RSSI_1, RSSI_2, \ldots, RSSI_m\}$ of RSSI values are collected in fingerprint location f at coordinates *(x,y)* from the nth receiving antenna, the true value of RSSI radio maps for each of the RFID receivers can be obtained by averaging the collected valid RSSI representation at the particular location, $f_{xy,n}$.

In the experiment, the presence of RSSI packet losses in each fingerprint location are expected due to the complex indoor signal transmission, signal obstruction by large furniture and equipment placement within the laboratory environment. In this paper, the value of α is used to represent any RSSI packet losses or invalid readings during the sampling process. However, the values of α within the RSSI data collection were not considered during the development of radio mappings. This results in incomplete radio mappings in a few fingerprint locations. As there are incomplete RSSI radio mappings, localization errors may be introduced in location determination. This error degrades the overall localization performance especially if the location of the localized object is determined based on the unique RSSI representation on a fingerprint location.

In order to evaluate the performance of RBF interpolated radio maps for fingerprinting localization, this paper tests two different reduced amounts of fingerprint location to build the radio mapping. The experiment considered both 95 and 171 fingerprint locations out of 225 total fingerprint locations available in the laboratory environment to complete the radio mappings based on the RBF interpolation methods. Both chosen amount of fingerprint locations represents 42% and 76% of the total fingerprint locations in the laboratory. The considered reduced fingerprint locations in the laboratory environment are shown in Figure 3.

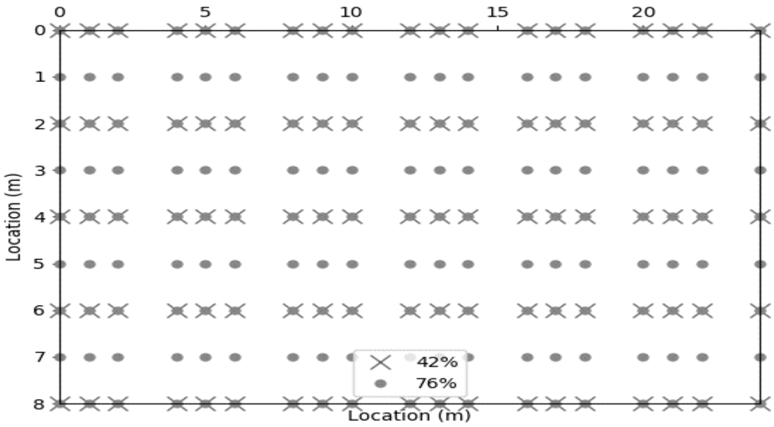


Figure 3. Reduced amount of fingerprint locations for RBF interpolated radio mappings estimation

Each of the fingerprint locations have shown their uniqueness in RSSI to represent their locations. Therefore, the usage of RSSI distance relationship model may not be suitable in this case as it may result in high errors in location determination. In order to reduce the errors in location determination, this paper suggests a probabilistic approach to estimate the RSSI radio maps with different RBF interpolation methods. The probabilistic approach is achieved by considering the Probability of Occurrence (POO) of the collected RSSI in every fingerprint location. The POO for any specific RSSI in a fingerprint location can be determined as shown in Equation 1.

$$POO_{RSSI} = \frac{no.of\ occurrence\ for\ specific\ RSSI}{no.of\ samples} \tag{1}$$

With the consideration of different POOs for every valid RSSI collected in every fingerprint location available in the laboratory environment, different probabilistic radio maps were generated using POOs in Equation 1. This results in a total of 180 probabilistic radio maps were generated in the valid RSSI range for four receivers. The generated probabilistic radio maps were fitted into Gaussian, Multiquadric and Inverse Multiquadric RBFs interpolation methods to compare the RSSI predictions with true RSSI values collected during the experiment. The estimation of RSSI radio mappings with different RBF methods are shown in Table 1.

Table 1 Different RBF functions for probabilistic radio mappings estimation

Types	Radial Basis Functions ϕ(r)	
Gaussian	$e^{-(\frac{D}{\beta})^2}$	(2)
Multiquadric	$\sqrt{\left(\frac{D}{\beta}\right)^2+1}$	(3)
Inverse Multiquadric	$\frac{1}{\sqrt{\left(\frac{D}{\beta}\right)^2+1}}$	(4)

Based on the equations in Table 1, D represents the distance between two different fingerprint locations and β represents the shape parameters of the RBF functions. With the consideration of different RBF interpolation functions for each of the available fingerprint locations, the RBF interpolated radio mappings cover all the 225 fingerprint locations and the highest probabilities of RSSI from different probabilistic radio mapping are being determined as the prediction on the RSSI at the fingerprint locations.

Unlike the conventional fingerprinting localization approach, this probabilistic approach requires fewer fingerprint locations to build the RSSI radio map. The performances of each estimated RSSI in the radio mappings with different RBF interpolation methods are compared with the conventional RSSI collected data. The average errors between RSSI for each of fingerprint locations for each of the radio mappings are shown as Equation 5.

$$\text{average } error_n = \frac{1}{m}\sum|RSSI^* - RSSI| \tag{5}$$

Where $RSSI^*$ and $RSSI$ represent the predicted RSSI and true RSSI collected at the valid fingerprint locations (m) respectively. Since there are four different radio mappings for four different receivers for both reduced fingerprint conditions, the errors between estimated RSSI and true value of RSSI were calculated based on each radio map representation.

3. RESULTS AND DISCUSSION

The true values of RSSI radio maps representation are achieved by collecting the RSSI values at each available fingerprint locations in the laboratory environment. However, the true values of collected RSSI radio mappings may be incomplete due to the presence of dropped packets, and the hardware placement within the environment as shown in Figure 4. In order to cover the whole RSSI radio mappings coverage for fingerprinting localization purposes, different RBF interpolation methods are investigated to predict the RSSI values at different fingerprint locations. For instance, the Gaussian RBF interpolated RSSI radio mappings based on 171 fingerprint locations for different RFID receivers in each of the fingerprint locations are shown in Figure 5, respectively.

Based on the interpolated radio mappings in Figure 5, the predicted RSSI values from the RBF interpolation functions covered every fingerprinting location available including the inaccessible locations within the laboratory environment. Thus, the completed RBF interpolated radio mappings could reduce the errors in location determination. With consideration of different RBF methods used in the experiment may result in different radio mappings, the average absolute error for each of the investigated RBF methods between the true RSSI and the predicted RSSI values in each of the fingerprint locations for respective radio mappings is determined with Equation 5.

The errors of RSSI prediction at every fingerprint location available for each radio mapping are shown in Figure 6. Based on Figure 6, although there are several high errors presence in certain fingerprint locations the reduction of 24% of the total time requirement to develop the RSSI fingerprinting radio maps is achieved with a reference of 76% fingerprinting location. The reduction of time requirement to develop the radio maps could be increased with lesser reference fingerprinting location. However, it is suggested that a trade-off is necessary between time, labour effort requirement for the development of radio maps and accuracies of the radio maps estimation. The performance of each of RBF interpolated methods for RSSI radio mappings estimations are tabulated in Table 2.

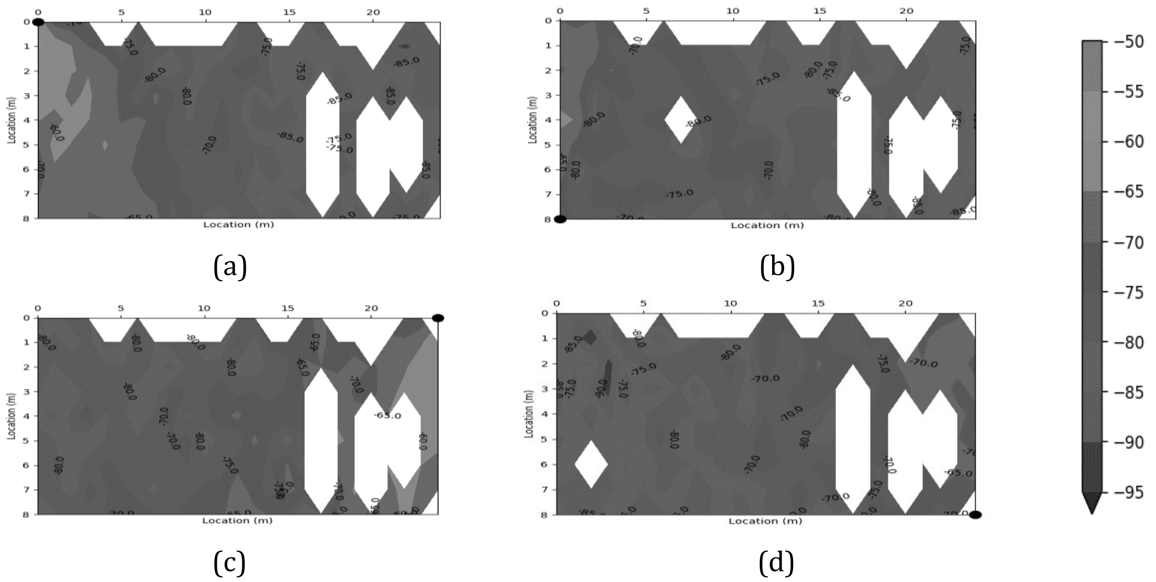


Figure 4. Average RSSI radio map representations for (a) receiver 1 (b) receiver 2 (c)receiver 3 (d) receiver 4

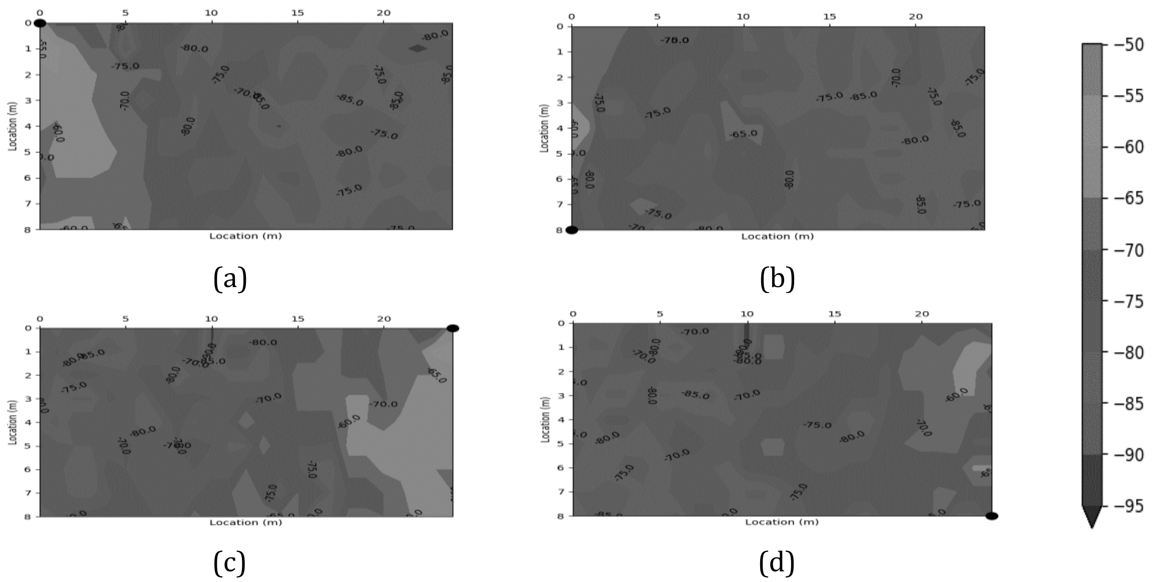
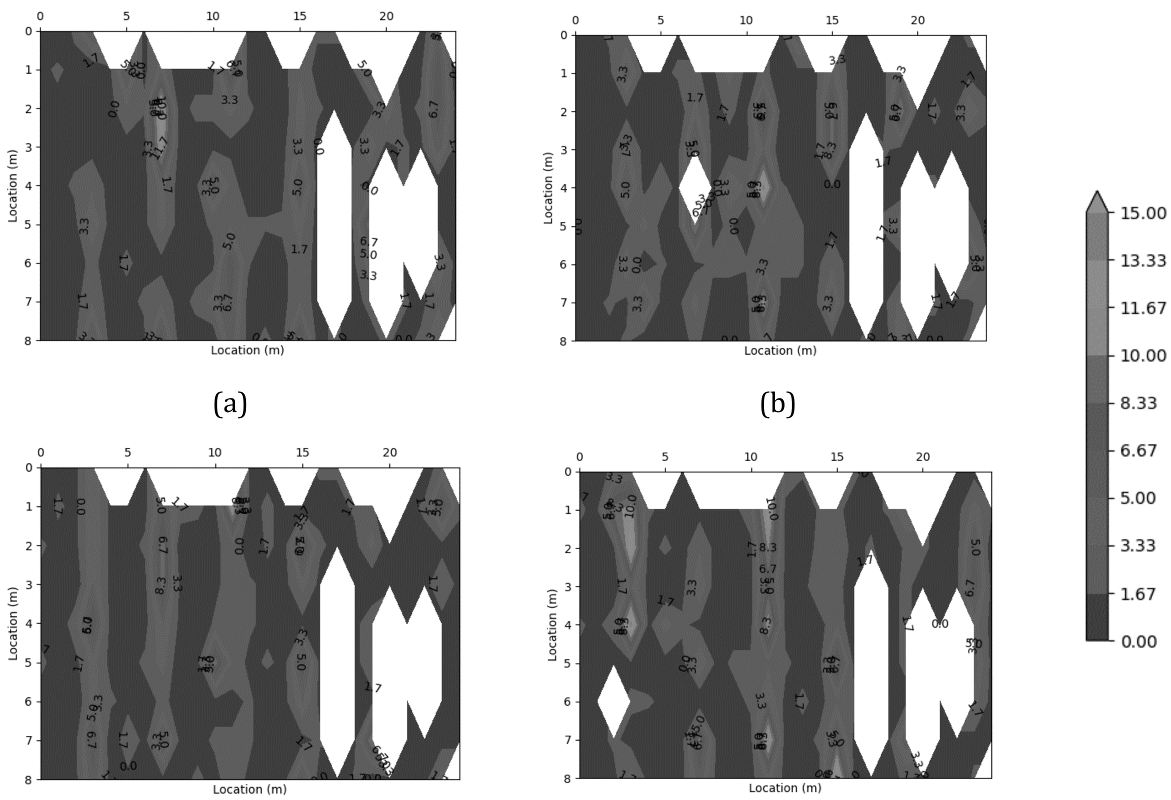


Figure 5. RBF interpolated (Gaussian) radio mappings based on 171 fingerprint locations for (a) receiver 1 (b) receiver 2 (c) receiver 3 (d) receiver 4



(a) (b)

(c) (d)

Figure 6. Errors plot for RBF interpolated (Inverse Multiquadric) radio mappings based on 171 fingerprint locations for (a) receiver 1 (b) receiver 2 (c) receiver 3 (d) receiver 4

Table 2 Average and mean errors for each RSSI RBF interpolated radio mapping

Types (β=0.3)		Average Error of RSSI for each Radio Mapping (dBm)				Mean error (dBm)
		Receiver 1	**Receiver 2**	**Receiver 3**	**Receiver 4**	
Gaussian	95 fingerprint locations (42%)	3.437	3.255	3.041	3.622	3.339
	171 fingerprint location (76%)	2.036	2.051	1.939	2.199	2.056
Multiquadric	95 fingerprint locations (42%)	3.345	3.311	2.924	3.714	3.324
	171 fingerprint locations (76%)	2.030	1.974	1.888	2.245	2.034
Inverse Multiquadric	95 fingerprint locations (42%)	3.315	3.296	2.751	3.612	3.244
	171 fingerprint locations (76%)	2.071	1.929	1.873	2.158	2.008

Based on the tabulated results in Table 2, the mean errors for four different radio mappings varied between 2.008 to 3.339 dBm in three different RBF interpolation methods for both conditions. It is noticeable that using a higher amount of reference fingerprint locations in the RBF interpolation methods would generate lower errors in radio mapping estimation. It was observed that the inverse multiquadric-based RBF interpolation method performs the best among its competitors with the mean error of 2.008dBm with 76% of fingerprint location is used to form the radio mappings. Meanwhile, the gaussian and inverse multiquadric-based RBF interpolated radio mappings achieved a slightly higher mean errors performance with 2.056 and 2.034dBm in four different radio mappings. However, it is suggested that the best RBF interpolation method is subjected to the laboratory conditions and structures.

It was observed that when the reference fingerprint locations are reduced to more than half of the originally available fingerprints, the mean error of the radio mappings estimation with RBF interpolation methods increased dramatically from around 1dBm to 2dBm. One of the possible reasons for this outcome is due to the unique presentation of RSSI in each of the fingerprint locations. The unique presentation of RSSI may not be able to reconstruct with RBF interpolation methods especially when the reference locations were reduced to more than half compared to its original available fingerprints. However, all of the RBF interpolation methods proposed in this paper are able to complete the RSSI radio mappings for fingerprinting localization even there are obstacles that may block the collection of RSSI data. The completion of RBF interpolated RSSI radio mappings is expected to reduce the errors in location determination of fingerprinting localization especially the uniqueness of RSSI in each fingerprint location observed in a complete radio map.

4. CONCLUSION

The work presented in this paper has demonstrated the feasibility of RBF interpolation methods for RSSI radio maps estimation. Among the RSSI radio maps estimation with different RBF interpolation methods, inverse multiquadric-based RBF interpolated radio mappings have achieved the best with the mean error of 2.008dBm for 225 fingerprint locations in four different radio mappings. Compared to other conventional RSSI fingerprinting localization methods, the RSSI radio maps formation with RBF interpolation methods required lower time and labour requirements to develop the RSSI fingerprinting localization radio maps. Throughout the experiments, the RBF interpolated radio mappings are observed with some error presence during the radio map estimation. However, it was suggested that it is the tradeoff between lower time and labor requirement and error presence in radio mapping estimation. The obtained RBF interpolated radio mappings will be further investigated in the future for their performance in object location determination within the environment.

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