Path Loss Model for Crowd Counting

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***Abstract*—Crowd counting using wireless sensing relies on either participatory or non-participatory methods. In both cases, the algorithm developed would predict the number of people or their density within the area monitored, for the purpose of crowd safety and management. An alternative to such approaches is the path loss modeling. A model is proposed to count the number of people by utilizing non-participatory (non-intrusive) technique supported by Design of Experiments (DOE) statistical method. The DOE method would identify the significant crowd properties that would inflict major signal losses and thus formulate the model. Results show that the proposed model has better accuracy compared to the other related works.**

Keywords—signal loss propagation; crowd monitoring; wireless sensor network; crowd modeling; design of experiments

I. INTRODUCTION

Crowd counting based on radio frequency is made practical with the advancement of personal and community-driven wireless technology. Crowd or people counting depend on wireless devices; which may either be carried by each person or deployed in non-intrusive placements, to sense the presence of humans. As humans traverse in an area, the disturbance of wireless signal is detected by the sensing devices. The magnitude of the said disturbance is then determined to estimate the number of people within the area.

There are several wireless techniques that have been proven successful in counting the number of people. The simplest method is by counting the number of smartphones as it can be easily assumed that a single device would represent a single person. For example, [1] used audio tones, [2] and [3] used Bluetooth while [4] used both Wi-Fi and Bluetooth which are readily available in current mobile phones. Another obvious method is the utilization of Radio-Frequency Identification (RFID) [5] where each RFID tag can be counted as a single person.

However, the detection range of these methods is generally low (Table 1), and a large number of dedicated participants is required, which would limit the feasibility of such application. An alternative is to employ the non-intrusive (device-free) technique that would no longer require users to carry any sensing devices. These are adopted in the works of [6]-[8].

From the device-free and fixed deployments, the signal loss pattern can be modeled. The signal path loss model consists of mathematical equations which attempt to estimate the signal propagation and attenuation. The information of the signal attenuation is then utilized to count the number of people.

Table 1: Related work on crowd counting

Related works	Standard / protocol	Radius of coverage (approx.)
Kannan, Venkatagiri, Chan, Ananda and Peh [1]	Audio tone	12 m
Weppner, Lukowicz, Blanke and Troster [2]	Bluetooth	10 m
Mowafi, Zmily, Abou-Tair and Abu-Saymeh [5]	RFID	3 m
Jin and Arora [9]	Bumblebee	10 m
Xi et al. [10]	Wi-Fi	8 m

II. RELATED WORKS

The path loss model calculates the reduction in power density of a wireless signal as it propagates through space [8]. Typically, in non-line of sight (NLOS), the path loss is modeled after the transmitter-receiver (T-R) distance, path loss exponent and shadowing effect caused by physical obstruction.

The path loss shadowing model can be traced back in the early works of [11]. The model is given as:

$$\mathrm{PL} = PL_0 - 10n \log_{10}(d) - X \tag{1}$$

where PL_0 is the received signal strength indicator (RSSI) at 1 m T-R separation, n is the path loss exponent, d is the T-R distance and X is the shadowing effect caused by the crowd.

From the data provided by [8], the path loss model of their system is plotted as shown in Figure 1, giving the exponential equation as:

$$PL = -74 + 44^{(-0.126x)} \tag{2}$$

Equation (2) indicates that the main parameter in incurring the RSSI loss is the body obstruction of the crowd. This simply means that a larger crowd would naturally inflict higher signal losses. In [8], the average signal loss incurred per person from a crowd of 30 people is 2.43 dBm.

On the other hand, the works of [12] defined the density of people by counting the number of people which gathered near a single point. In essence, their actual technique in determining the crowd size is by mapping the average RSSI recorded by each node to the number of people and then summing them together. However, the level of crowd density or the number of people could not be connected to the RSSI data as the information was not disclosed. Nevertheless, the authors provided the formulation of the Knife-edge diffraction path loss algorithm which is given as:

$$PL = 6.9 + 20\log\sqrt{(v-0.1)^2+1} + v - 0.1 \qquad (3)$$

$$v = h\sqrt{\frac{2}{\lambda}\left(\frac{1}{d_1}+\frac{1}{d_2}\right)}$$

where v is the Fresnel parameter, h is the height of the tag above direct LOS, λ is the wavelength, d_1 and d_2 is the distance from the receiver and transmitter to the node respectively. The formula still allows the prediction of signal loss in terms of T-R distance and height of the node.

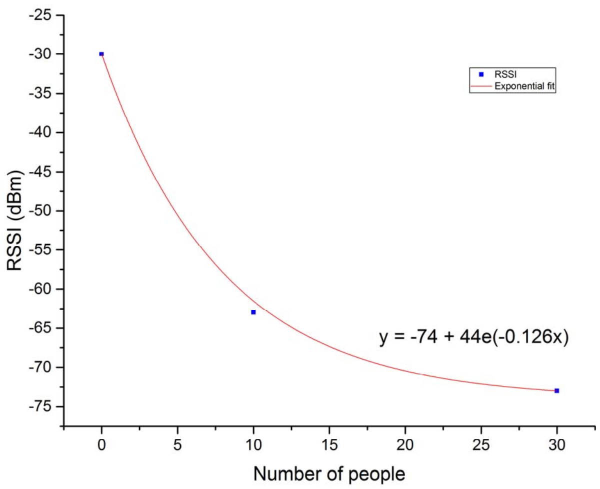

Figure 1: Exponential fit for the data on signal loss versus crowd size provided by [8]

III. Methodology and Implementation

The path loss model from (1) is modified as:

$$PL = PL_0 - 10n\log_{10}(d) - RSSI_{crowd\_pattern} - BAF \qquad (4)$$

where $RSSI_{crowd\_pattern}$ and BAF represents the average signal loss incurred by the effects of crowd pattern and the body attenuation factor; the effect of crowd size on signal attenuation respectively. The crowd pattern is defined as the difference between scattered and lumped crowd when the proximity between an individual to the other is 0.30 and 0.65 m respectively. This definition is based on the spatial distance between people in a 1 m^2 area.

The introduction of these two parameters ($RSSI_{crowd\_pattern}$ and BAF) stems from the results of the DOE method conducted in a previous work [13]. Both crowd pattern and size were identified to be significant parameters in inflicting the loss of signal in crowded environment.

The site under study is 30 m in length and 5 m in width for a total area of 150 m^2 (Figure 2). This represents a single grid in the proposed deployment. The 150 m^2 area also matches the area of study by [6]. However, the work of [6] requires 21 transceivers as opposed to only 4 proposed by this research. Whereby [8] deployed their system in a 96 m^2 area.

The sensing capabilities of the related systems are tabulated in Table 2. The proposed system of this research increases the wireless coverage to 30 m and thus lessened the number of nodes required for crowd detection.

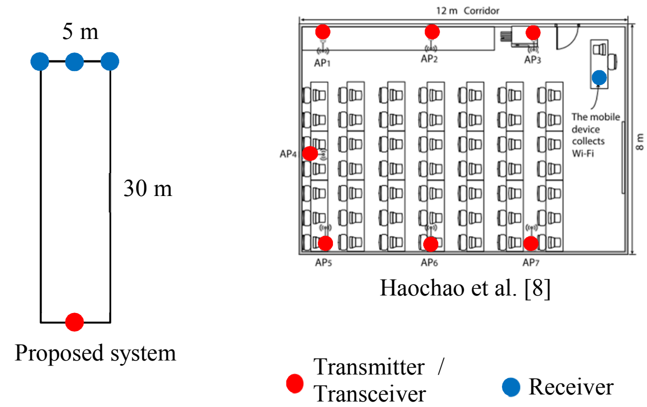

Figure 2: Layout of the related works

Table 2: Comparison between deployments of the proposed system with related works

Authors	Crowd size (people)	Detection radius per node	Node density
Proposed	50	30 m	1 per 37.5 m^2
Haochao et al. [8]	50	~12 m	1 per 12.0 m^2
Hiroi, Shinoda and Kawaguchi [12]	40	~10 m	Not disclosed

The transceivers utilized consist of Arduino-based microcontrollers and ZigBee-based modules with NLOS capabilities of up to 60 m. A total of 15 people participated in the survey and the average losses inflicted were calculated along with their standard deviations to produce a linear graph. The graph is then extrapolated to estimate the RSSI of up to 50 people.

IV. Results and Discussions

The relevant parameters obtained from the experiments conducted to satisfy the path loss models (2)-(4) are tabulated in Table 3. The *BAF* of the proposed model is defined as 0.84*m*, where *m* is the number of people and 0.84 is the average signal loss inflicted by body obstruction measured from three receivers in dBm unit.

Thus, (4) is finalized as:

$$PL = PL_0 - 10n \log_{10}(d) - RSSI_{crowd\_pattern} - 0.84m \qquad (5)$$

where PL_0 is -32 dBm, path loss exponent, n measured at 30 m of line-of-sight of the T-R separation is 1.02, $RSSI_{crowd\_pattern}$ is -2.57 dBm and multiplying m, the number of people, with 0.84 is the average body attenuation factor measured from three receivers.

Table 3: Relevant parameters for the modelling

Parameter	**Value**
d	30 m
PL_{30m}	-47 dBm
PL_0	-32 dBm
n	1.02
m	0.84
λ	0.125 m
h	0.3 m
d_1 and d_2	15 m
$RSSI_{crowd\_pattern}$	-2.57 dBm
BAF	0.84 *m*

The comparison between the models with the empirical data is imaged in Figure 3. The graphs show that the proposed model could fit the actual data better compared to [8] and [12]. The results are further clarified in Table 4. An RSSI difference of around more than 4.5 % compared to the actual data would produce an incorrect estimation. This is as highlighted in red in the table. Overall, the proposed model has the least percentage error in predicting the size of the crowd. This is attributed to the inclusion of both crowd size and pattern that increases the estimation accuracy.

Haochao's model [8] only considered the signal loss by body obstruction (crowd size). Morever, the model does not fit the actual data as the experimental data fits a linear line. Hiroi's model [12] relies only on three variables; the range between T-R separation, the frequency and the height of the node whereas the rest are constants. Hiroi's model disregarded the effect of crowd properties and this resulted in the inaccuracies.

In summary, the proposed path loss model is able to estimate better the number of people compared to other methods. The proposed model allows crowd counting with higher accuracy to monitor the size of the crowd in the designated area.

V. Conclusion

The proposed path loss model introduces the crowd pattern parameter in addition to the crowd size in estimating the number of people within the crowd. Results show that the proposed model could accurately count the number of people in the monitored area. This allows crowd size prediction that may complement to the existing crowd monitoring and density estimation systems.

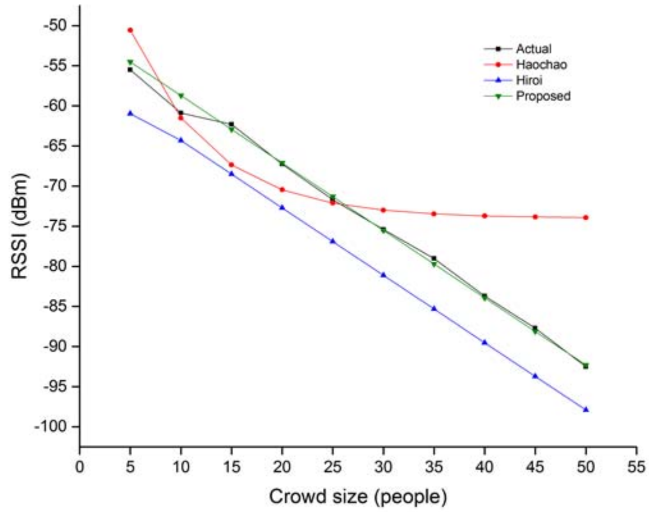

Figure 3: Comparison between the proposed prediction model with the actual and other models.

Table 4: RSSI difference (diff.) between the models compared to the actual data and the resulting estimation (Est.) of the number of people (red font indicates incorrect prediction)

# of people	**Proposed**		**Haochao et al. [8]**		**Hiroi, Shinoda and Kawaguchi [12]**	
	RSSI diff. (%)	Est. (people)	RSSI diff. (%)	Est. (people)	RSSI diff. (%)	Est. (people)
5	1.77	5	8.89	5	9.83	10
10	3.58	10	1.02	10	5.61	15
15	0.99	15	8.11	20	9.98	20
20	0.20	20	4.77	25	8.13	25
25	0.52	25	0.56	25	7.29	30
30	0.14	30	3.21	30	7.56	35
35	0.87	35	7.04	30	7.96	40
40	0.23	40	11.96	30	6.92	45
45	0.45	45	15.82	30	6.83	50
50	0.23	50	20.11	30	5.82	55

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