Human Location Classification for Outdoor Environment

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Abstract. Outdoor localisation can offer great capabilities in security and perimeter surveillance applications. The localisation of people become more challenges when involving with the non-linear environment. GPS and CCTV are two localisation techniques usually use to localise human in an outdoor environment. However, they have weaknesses which result in low localisation accuracy. Therefore, the application of Device-free localisation (DFL), together with the Internet of things (IoT) is more appropriate due to their capability to detect the human body in all environmental conditions, and there is no problem losing signals as faced by GPS. This system offers excellent potential in humans localisation because humans can be detected wirelessly without any tracking device attached. In developing the DFL system, the main concern is the localisation accuracy. Although the existing DFL system gives significant result to the localisation, the accuracy is still low due to the large variation in RSSI values. Hence, a Radio Tomographic Imaging-based ANN classification (RTI-ANN) approach is proposed to increase the localisation accuracy. This Artificial Neural Network (ANN) is designed to learn the Radio Tomography imaging (RTI) input for classification purpose. Even though the RTI gives a good result to the localisation, however, it suffers from smearing effect. To eliminates this smearing area and background noise, pre-processing of the RTI image is required. Thus, extracting the valuable information technique from the RTI image has been proposed. By extracting the valuable information data from the RTI image, about 61\% to 66\% of the smearing noise is removed depending on the size of the RTI image. Only data directly associated with human attenuation used for training and learning of ANN. The experimental results show ANN system can localise human in the right zone for a given dataset.

Keywords: device-free localisation, radio tomographic imaging, noise elimination, neural network
1. Introduction

Device-free localisation (DFL) has attracted remarkable attention, especially in the security monitoring system in the past few years. Internet of thing (IoT) with wireless technologies in DFL system offers great capability, especially in collecting and transmitting data to processing units. The implementation of IoT and wireless technology in DFL (e.g. Finger-print and Radio Frequency Tomography) makes human localisation easier without any touch with the target (human). Based on wireless sensor networks (WSN), the target is free from wearing a tracking device that makes human localisation easier without any contact with the target (human) [1].

Various wireless localisation techniques have been developed to localise the human position, which enables the transducers to send and receive data without any physical connection. These approaches characterised the differences of Radio-frequency (RF) response by exploiting the radio frequency attenuation due to obstruction of the human body. However, the identification of the human position become inaccurate due to a large variation in radio signal strength (RSS) [1]. Meanwhile, if there have small changes in multipath components, e.g. node position changes and environmental factors, the value of RSSI measurements will be affected [2][3]. Based on the fundamental of radio propagation, the received signal power varies as a function of space, frequency and time. The variation of the received signal in small free space outdoor environment can be classified as small scale fading because it deals with a small distance between transmitter and receiver [4]. The main cause that affects the signal strength is the multipath propagation of the electromagnetic wave. As the distance between transmitter and receiver increase, the local average of the received signal power decreases gradually.

Unlike the Finger-print approach, the Radio-frequency tomography (RFT), usually known as Radio Tomographic Imaging (RTI) considers all the multipath problems in the measurement of the attenuation field. However, this technique suffers two major problems. First, an ill-posed problem happens when the number of pixel in the reconstruction image is greater than the number of projection data [2]. Second, the overlapping of images due to the summation of the back-projected signals for each pixel causes the smearing effect. Due to these problems, the conventional RFT system applies regularisation techniques. However, if the parameter of regularisation selected is not suitable, it will affect the image result [5][6][7][8].

The problem in classification is caused by the DFL problem, in which location and RSS relationships are not directly accessible. Researchers start to tune their focus to solve the classification problem by introducing several machine learning approaches to extract the features for classification purpose. The popular machine learning algorithm used include K-Nearest-Neighbor (KNN), Support Vector Machines (SVM) and Neural Networks. Among this three, Neural Networks give a significant impact on localisation accuracy [9][10]. However, it still has a problem of low accuracy because of data source influenced by environmental noise. Therefore, this paper presents RTI-ANN classification approach as an alternative solution to overcome the localisation problem. In this RTI-ANN classification approach, the pre-processing of the RTI image has been introduced.

2. RSSI ATTENUATION

In this DFL-RTI system, each sensor will act as a transceiver, which can transmit and receive the data. The number of link's measurements (M) can be obtained by

\[ M = \frac{n(n-1)}{2} \] (1)
Where \( n \) is the number of the transceiver allocate around the monitoring area. By assuming that the measurement is reciprocal due to two-way communication of sensors, therefore, total measurement is divided by two. The average of RSS values is calculated to minimise the variation of RSS data for a set of samples, for each link. Before we convert the RSS data into a matrix form, the data need to be normalised first. This normalisation process is important to ensure that all the data is visible and read in the same way across all records. Mathematically, the normalisation of measurement data, \( N_{(Tx,Rx)} \) can be defined as

\[
N_{(Tx,Rx)} = \frac{M_{(Tx,Rx)} - M_{ref}}{M_{ref}} = \Delta y
\]

(2)

where \( M_{(Tx,Rx)} \) is attenuation data for current human position, and \( M_{ref} \) is reference data during an empty area. Next, we set the normalised ratio to a certain threshold value. If the normalised ratio \( N_{(Tx,Rx)} \) is less than the threshold value, normalized data is set to be zeros. Thus, we can generate the unique dataset of each location.

\[
M = \begin{cases} 
1 & \text{if } N_{(Tx,Rx)} > \text{threshold value} \\
0 & \text{if } N_{(Tx,Rx)} < \text{threshold value}
\end{cases}
\]

(3)

Figure 1 illustrates the type of projection used in this research. Fan-beam projection is chosen to maximise the coverage areas of detection.

![Figure 1. Fan-beam projection for data measurement](image)

The attenuation (\( S \)) can be modelled as

\[
S_i(t) = \sum_{j=1}^{h} \omega_{ij} x_j(t)
\]

(4)

where \( x_j(t) \) is a single link attenuation, and \( \omega_{ij} \) is the weight for each link. All parameters in (4) compiled into matrix form. Vector RSS (\( y \)) can be obtained by multiply the weight of each link (\( W \)) with attenuation vector (\( x \)) and can be expressed as:

\[
\Delta y = W \Delta x + n
\]

(5)

where \( \Delta y \) is the vector of length \( M \) (contain with RSS for all link) and \( \Delta x \) is the image of attenuation to be estimated. The weighting (\( W \)) can mathematically describe as
\[ \omega_{ij} = \begin{cases} \frac{1}{\sqrt{d_{ij}}} & \text{if } d_{ij1} + d_{ij2} < d_{ij} + \lambda \\ 0 & \text{otherwise} \end{cases} \]  

where \( \lambda \) is a parameter that determines the ellipse's width, \( d_{ij1} \) and \( d_{ij2} \) are distances between the centre of a pixel to both points of Tx and Rx, respectively. Thus, the pixels will have non-zero weighting values if and only if their centroid falls within the ellipse [11] as shown in Figure 2.

3. Localisation-Based - RTI-ANN Classification Approach

The block diagram in Figure 3 shows the Localization System using RTI with ANN classification approach, called an RTI-ANN technique. First, the calibration process is conducted to ensure the data is valid before we measure the attenuation and is saved as a reference dataset. All measured data were compared with the reference dataset to obtain the attenuation data. This approach provides the measurement vector for image reconstruction.

An Artificial Neural Network (ANN) is designed to learn the Radio Tomography imaging (RTI) input. This ANN classification approach is used to increase the localisation accuracy. In this research, the RTI data has been used as an input dataset to this ANN system. Since RTI image contains un-informative data, extracting valuable information from radio tomography imaging (RTI) is required to eliminate background noise and smearing effect. This extracting information is known as RTI data. The background noise can be removed using image filtering techniques. Training and test ANN is conducted to evaluate the system performance. The ANN will execute all data and classify it according to the designated position class, as stated in Table 1.

![Figure 2. Ellipse model for weighting calculation](image)

![Figure 3. Localization System using RTI - ANN classification approach](image)
3.1. Experimental Design

An experiment has been conducted to gather information about the human body attenuation. The information about RSS data for both stage (calibration and attenuation) help in designing the system model. By taking the average diameter of the human body is 50cm, monitoring area of 5m x 5m has been divided into nine grid to represent a zone, as shown in Figure 4(a). Hence, each zone can contain up to four positions of human. The reason for zoning the monitoring area is to fix the human position in a specific location to ease classification work.

![Figure 4](image)  
(a) 9 zone of monitoring area

![Figure 4](image)  
(b) Affected pair of links due to human presence

**Figure 4.** Experimental design for human localization

![Figure 5](image)  
**Figure 5.** Sensor array follow experimental design

Figure 4(b) shows the affected pair of the link, which gives high attenuated data. Where the area in the circle contains high attenuated data which presents the human position in the monitoring area. Figure 5 shows the experimental setup for monitoring area of 5m x 5m. The RSSI value of the baseline dataset collected under the calibration period (without the presence of human). Based on the experiment, the range of RSSI without human body attenuation is around -40 to -60 dBm, while the human body attenuates about -61 dBm to -80 dBm.
3.2. Pre-processing of RTI image

Linear back projection (LBP) technique is used to reconstruct the tomographic image. As can be seen from Figure 6(a), the image is slightly blurred, which is due to the smearing effect that can affect localisation accuracy. Technically, the colour in the RTI image represents the intensity or permittivity of the subject. If we focus on the outer layer of the RTI image, we can see the smearing effect on it. Therefore, the elimination of background noise is needed. Now, let us focus more on the centroid of the RTI image. The image filtering technique has been applied to eliminate the smearing area; By assuming that the centre of the RTI (blue) image has a high permittivity value that may represent human, undesirable data can be automatically removed as shown in Figure 6(b). This approach can be proposed to classify human location.

![RTI image before and after eliminating the background noise](image)

**Figure 6.** The RTI image before and after eliminating the background noise

4. Classification Approach

Figure 7 illustrates the frameworks of RTI-ANN classification approach. Since the RTI data contain the specific pattern associated with the human position, the classification approach will match the similarity of the data. ANN used as a training and learning tool for high accuracy detection. As usual, Multi-Layer Perceptron (MLP) of ANN calculates the position based on the RTI. There are three layers of MLP, the input layer, the hidden layer, and the output layer. Where in most practical application, one hidden layer is sufficient for all input nodes [12].

![Frame work of RTI-ANN Classification Approach](image)

**Figure 7.** Frame work of RTI-ANN Classification Approach
The Forward formulation for each hidden node's input can be expressed as:

$$a_k^h = \sum x_n w_{k,x}^h + b_k^h$$  \hspace{1cm} (7)$$

where \(x_n w_{k,x}^h\) are weight’s connection from input layer’s node and \(b_k^h\) is a bias node.

Next, this hidden node’s input will be transformed by Rectified Linear Unit (ReLU) activation function to compute the MLP output. Comparing to sigmoid and other activation functions, ReLU model is more simple and straightforward. The activation function is formulated in (8), and it works under specific conditions, as stated in (9).

$$h(a) = \max(0, a)$$ \hspace{1cm} (8)

$$S = \begin{cases} 
1 & \text{if } h(a) > 0 \\
0 & \text{otherwise}
\end{cases}$$ \hspace{1cm} (9)

The MLP will learn indirect tomography images from RTI data. This approach will allow the ANN system to recognise the unique pattern of the entire dataset by calculating the probability distribution for each node and selecting the highest probability node to represent the human position in a given localised area. ANN system classifies human position based on a specific zone, as mentioned in Table 1. Each zone contains four positions of human. The idea is if a human move from one location to another location in the same zone, ANN will classify it as in the same zone.

| Zone | Position | Class |
|------|----------|-------|
| 0    | 1,2,3,4  | 0     |
| 1    | 5,6,7,8  | 1     |
| 2    | 9,10,11,12 | 2   |
| 3    | 13,14,15,16 | 3   |
| 4    | 17,18,19,20 | 4   |
| 5    | 21,22,23,24 | 5   |
| 6    | 25,26,27,28 | 6   |
| 7    | 29,30,31,32 | 7   |
| 8    | 33,34,35,36 | 8   |

5. Results of Classification Model

This section presents the results of ANN classification for given RTI dataset. The performance of ANN is achieved 100% for training and testing, as shown in Figure 8. On the other hand, loss of validation for training and testing decreases gradually towards zero. A different set of RTI data is used for validation to verify the ANN model. A summary of the results is as listed in Table 2. From this validation stage, the result shows that the classification is successful where the model can localise human correctly in the right zone for a given dataset.
Table 2. Human localisation for different zone area

| No. | Position | Zone   |
|-----|----------|--------|
| 1   |          | 0      |
| 2   |          | 4      |
| 3   |          | 3      |
| 4   |          | 1,3,5,7|
| 5   |          | 0,2,6,8|
6. Conclusion

This paper presents the RTI-ANN classification approach. From these results, we can say that RTI performance improved in terms of accuracy of localisation by integrating RTI system with the ANN approach. Removing the smearing area and background noise can help to improve localisation accuracy. Further work will focus on the exploration of the Deep learning approach to characterise human positions from two different datasets.

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