Emergency Rescue Localization (ERL) using GPS, Wireless LAN and Camera

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Abstract

Congestion avoidance in emergency situations is among one of many overlooked localization issues. During emergency situations (such as fires), sometimes the rescuers find it hard to find the best exit route from the inside to the outside of a building. Any time delay in decision making will risk the loss of lives. Therefore, an efficient Emergency Rescue Localization (ERL) system is needed to help rescuers find the best route from the inside to the outside of a building. Thus, we propose a new ERL that is based on the integration of a Global Positioning System (GPS), Wireless LAN and camera. In this proposed ERL, the integrated Wireless LAN (WLAN) and Camera are used to retrieve location information inside a building. Then, localization methods will be adapted to GPS-based localization when subjects are in open areas outside the building. Finally, we present our experimental results to illustrate the performance of the localization system for indoor and outdoor environment set-up.

Keywords: Wireless LAN, Resource Localization, Emergency Response, GPS

1. Introduction

Many applications of Wireless Sensor Networks (WSNs) addressing emergency response domains were reported recently [1-6]. One of the most convenient aspects of WSNs are that they are convenient to deploy as well as to maintain. So, in some specific scenarios, WSNs than wired infrastructures. In previous works [7-11], researchers have attempted to solve the problem of navigating a single person out of dangerous areas through the shortest and safest path with the help of the WSN assisted infrastructure. However, the evacuation applications assisted by the WSN might not be able to find a safe exit for the evacuees in real time emergency situations [12-16]. Consequently they have to wait for rescuers to remove obstacles in time. As any spot may turn dangerous at any time, longer waiting times mean less chance of survival [17, 18]. Additionally, rescuers, another main force in emergency rescue, can provide great contribution in saving people out of disasters [19-21]. Nevertheless, although they could reach the emergency site very quickly, they may not know the situation inside. For example, where the trapped people are, whether there is congestion, and which paths can be used to alleviate congestion could be unknown to the rescuers. Providing more inside information to rescuers with the help of WSNs can greatly improve the efficiency of the emergency rescue. Therefore, we propose a new Emergency Rescue Localization (ERL) system which takes both pedestrian congestion and rescuer’s actions into account. The remainder of the paper is organized as follows; Section 2 summarizes related works. Section 3
describes our problem formulation. Section 4 presents design details of the ERL. We present our simulation results in Section 5. Finally, we conclude the paper in Section 6.

2. Related Works

Emergency localization determination and guidance for evacuees with WSNs are addressed in quite a few works such as [22-26]. In [26], the shortest path to exit is offered to evacuees and people are divided into two groups according to their position: in or out of dangerous regions. Only a subset of sensors are used in order to reduce the communication cost. Based on the work of [26], more kinds of sensors are added into WSNs and the protocol is extended to 3D environments in [24]. Distributed algorithms are proposed in [26] to guide a target across a region for self-organized sensor networks. In addition, there are researches that propose to navigate people following the safest and shortest path using directed road maps [22]. They use medial axis of safe regions to build a road map and assign directions on it, which also helps to lower the overhead of packets. In [23], they utilize the skeleton graph to abstract the localization field which is different from the road map mentioned in [22]. Additionally, some other works tried to offer help to rescue forces. Methods proposed in [27, 28] provide useful information to rescuers. In [27], underground collapses can be detected through regulating the deployment of WSNs. In [28], a method is proposed to help rescuers to work more effectively by narrowing down searching region in wild areas. The authors use witness information offered by other hikers to find possible locations of victims. In addition, the researcher [29] developed a network of distributed mobile sensor systems as a solution to the emergency response problem, where robots are used to look for immobile people trapped by fire. However, they do not consider pedestrian congestion. Meanwhile, in most scenarios such as indoor environments, limited space and a lot of evacuees tend to cause congestion (some emergencies might make some usual transport systems, for example elevators, fail to work). Thus, congestion should not be neglected in emergencies. Our proposed ERL takes both congestion and rescuer team actions into account in order to evacuate people in emergency situations more efficiently. The remainder of the paper is organized as follows: Section 2 summarizes related works. Section 3 describes our problem formulation. Section 4 presents design details of the ERL. We present our simulation results in Section 5. Finally, we conclude the paper in Section 6.

3. Problem Formulation

There might be several dangerous areas in a building during an emergency, which are threats to human safety, (for example: fire, smoke, obstacles, etc., [30, 32]). Thus, people need to evacuate the building as quickly as possible while keeping away from those dangerous areas [33, 34]. Though it is the safest path to the exit, some people may be obstructed by congestion. In addition, once someone is trapped in dangerous areas, the system is unable to output any path. The use of single localization technique is useless, since it might be obstructed by any object such as fire, obstacle, smoke and people. To make it practical, multiple localization method is needed. However, it seems to make end users feel difficult with regard to device integration. Thus, the integration of localization sensors between internal mobile phone sensors (such as GPS, WLAN, camera or Bluetooth) is needed to solve this issue. The reason is, the integration can promote mobility for end users. The combination between radio frequency-based sensors (ex: GPS or WLAN or Bluetooth) with imaging sensors (Camera) may lead to propagation and illumination error issues. Here, we focus on illumination error issues since this error can cause failure of the overall performance system in delivering positioning information. Assumptions and objectives of our design are presented as follows.
4. Assumptions

We assume that a region under emergency has several dangerous areas, and each dangerous area might emerge, disappear, expand or shrink at any time. The WLAN access point deployed in the region can sense the environment around them. Each access point knows all the IDs of its neighbours and whether it is in a dangerous area or not. We assume each user carries a communication device such as a compatible PDA which is able to communicate with access point surroundings. Besides that, this device must also be equipped with a mobile camera and embedded GPS for image tracking and outdoor localization purpose. We also assume that all firemen can keep in touch with the control centre.

5. Objective

We aim to propose a new ERL based on the integration of GPS, WLAN and camera on a mobile phone architecture. By implementing this system, locations both inside and outside a building which are more pervasive can be determined with ubiquity in various environments. Apart from that, location can also be determined in illumination environments when users are inside the building.

6. System Integration Design

Our concept is to determine localization by using a mobile phone without external sensor integration (see Figure 1 for our proposed system design). The reason is to ensure that the ERL system can be used by rescuers without difficulties in device integration. There are three (3) types of mobile sensors used, which are; GPS, WLAN and a camera. GPS is used to retrieve location information when rescuers are outside a building. When it comes to the inside of the building, the location information will be switched onto indoor positioning sensors (WLAN/Camera). Input from the camera will be extracted in order to obtain the feature interest (corner) and at the same time, input from the WLAN will be extracted in order to gather WLAN Localization coordinates. This type of information will be sent directly through wireless networks to the server. In the server, the image input will firstly be processed by illumination algorithm in order to reduce illumination error in the image input. Then, it will be processed by the image segmentation method before it is processed through the corner detection process in order to get the feature interest point. After the image information processing, this interest point image will be matched with coordinate information obtained from WLAN localization using the model fitting approach.
6.1. GPS Localization

In GPS positioning, we prefer to use Relative-Interpolation method, since the coordinates of the reference point are not the absolute longitude and latitude. Let $x_{lat}$ and $x_{long}$ be the longitude and latitude of the reference point $x$ (A or B), and $x_x$ and $x_y$ be it’s x and y coordinates, respectively. Let C be the unknown user’s current position and $c_{lat}$ and $c_{long}$ be the GPS data measured at the user’s current position. Then, we estimate the user’s $x$ and $y$ coordinates on the map, $c_x$ and $c_y$ respectively, with the equations below:

$$C_x = \left(\frac{c_{lat} - A_{lat}}{B_{lat} - A_{lat}}\right) (B_x - A_x) + A_x \quad (1)$$

$$C_y = \left(\frac{c_{lat} - A_{lat}}{B_{lat} - A_{lat}}\right) (B_y - A_y) + A_y \quad (2)$$

6.2. Wireless LAN Localization

We aim to propose a new ERL based on the integration of GPS, WLAN and camera on a mobile phone architecture. By implementing this system, locations both inside and outside a building which are more pervasive can be determined with ubiquity in various environments. Apart from that, location can also be determined in illumination environments when users are inside the building. In wireless LAN localization, we prefer to use a well-known WLAN fingerprinting method known as RADAR [35]. In the RADAR WLAN Localization system, there is a searching algorithm, which is in the main part of the system, known as KNN nearest neighbour [36]. This algorithm contributes a look-up table during the off-line phase. However, WLAN signal strength also suffers in the obstructed environment since the signal will propagate and be lost if there is a blockage between the AP and the mobile device receiver. Theoretically, the WLAN signal path loss obeys the distance power law as described below:
\[ P_r(d) = P_r(d_0) - 10n\log\left(\frac{d}{d_0}\right) + X_\sigma \]  

Where \( P_r \) is the received power; \( P_r(d_0) \) is the received power at \( d_0 \) (called as reference distance), \( n \) is the path loss exponent, which indicates that the rate of the path loss increases with distance. It depends on the surroundings, building type and other obstructions. \( d_0 \) is the close-in reference distance (1m) and \( d \) is the distance of separation between the RF signal transmitter and receiver (The transmitter could be AP and receiver could be mobile device receiver). The term \( X_\sigma \) is a zero mean Gaussian random variable with standard deviation \( \sigma \). Equation (3) is modified to include the Wall Attenuation Factor \( (WAF) \). The modified distance power law is given as (4),

\[ P_r(d) = P_r(d_0) - 10n\log\left(\frac{d}{d_0}\right) - T*WAF \]  

Where, \( T \) is the number of walls between transmitter and receiver.

\[ d = e^{\frac{(P_r(d_0) - P_r(d) - T*WAF)}{10}} \]  

Equation (5) has been derived from equation (4). This equation is to measure the distance between the Access Point and Mobile Node. When the mobile device or node location has been calculated, the distance of every device or node will be calculated using the Euclidean Distance equation (6).

\[ \text{Distance} = \sqrt{(X_1 - X_2)^2 + (Y_1 - Y_2)^2} \]  

The Location Server will calculate the distance for every device in the network and compare all distances to find which the nearest device from the mobile node chosen. The nearest computation method is done by nearest neighbour(s) in signal space (NNSS). The idea is to compute the distance (in signal space) between the observed set of SS measurements, \((ss_1, ss_2, ss_3)\) and the recorded SS, \((ss_1', ss_2', ss_3')\) at a fixed set of locations, and then pick the location that minimizes the distance. In order to calculate based on three \( (3) \) measurements, the equation (6) can be inherit to become as equation (7) where \( D \) is the distance between the observed signal and the recorded signal;

\[ D = \sqrt{(ss_1 - ss_1')^2 + (ss_2 - ss_2')^2 + (ss_3 - ss_3')^2} \]  

6.3. Inverse Intensity Chromaticity Space

In the inverse-intensity chromaticity space, it is assumed that the average reflectance in a scene is achromatic. The correlation between image chromaticity and illumination chromaticity becomes equation (8),

\[ I_c' = \sigma_c - p \frac{1}{\Sigma I_i} \]  

This equation is the core method of inverse-intensity chromaticity space. It shows that by solely calculating the value of \( p \), the illumination chromaticity \( (I_c) \), can be determined since image chromaticity \( (\sigma_c) \) and total image intensity \( (\Sigma I_i) \) can be directly observed from the input image. However, if the values of \( p \) are constant and the values of \( \Sigma I_i \) vary throughout the image, the last equation becomes a linear equation, and the illumination chromaticity \( (I_c) \) can be estimated in a straightforward manner by using general line fitting algorithms. However, in most images, the values of \( p \) are not constant, since \( p \) depends on \( m_d, A_c \) (defuse chromaticity) and \( I_c \) which can be described as equation (9).
\[ p = m_d(A_c - \Gamma_c) \]  \hspace{2cm} (9)

For the sake of simplicity, the assumption that the values of \( A_c \) are constant, makes the values of \( p \) depend solely on \( m_d \), as \( \Gamma_c \) has already been assumed to be constant. The value of the \( m_d \) can be obtained by using this equation (10).

\[ m_d(x) = w_d(x) \sum B_1(x) \]  \hspace{2cm} (10)

The value of \( w_d(x) \) is a geometrical parameter for diffuse and specular reflection, respectively; depending on the geometric structure of the location (x). The value of \( \sum B_1(x) \) can be determined using equation (11) (assume \( A_c(x) \) as constant as mentioned previously).

\[ \sum B_1(x) = \frac{B_c(x)}{A_c(x)} \]  \hspace{2cm} (11)

On the other hand, the value of \( B_c(x) \) can be determined using the equation below in which \( E(\lambda) \) is the illumination spectral distribution, \( q_c(\lambda) \) is a three-element-vector of sensor sensitivity with index representing the type of sensors (r,g,b) and \( S_d(\lambda,x) \) is a diffuse spectral reflectance function (refer to equation 12).

\[ B_c(x) = \int_{\Omega} S_d(\lambda,x)E(\lambda)q_c(\lambda)d\lambda \]  \hspace{2cm} (12)

### 6.4. Mean Shift Segmentation

The mean shift segmentation basically used in this research is to segment the image which is captured by mobile camera. The mean shift segmentation in the spatial-range domain has the same simple design as the filtering process. Assuming the data (input) to be normalized with \( (\sigma_s, \sigma_r) \). Let \( \{x_j\}_{j=1}^{n} \) be the original image points, \( \{z_j\}_{j=1}^{n} \) (be the points of convergence) and \( \{L_j\}_{j=1}^{n} \) (a set of label scalar). The detail of mean shift segmentation algorithm can be shown as Fig. 2. Let \( \{x_j\}_{j=1}^{n} \) and \( \{x_j\}_{j=1}^{n} \) be the d-dimensional original and filtered image points in the spatial-range domain. The input data is assumed to be normalized with \( \sigma_s \) (for the spatial part) and \( \sigma_r \) (for the image range). This process can be shown as Fig. 3 as the mean shift filtering algorithm. In the final step of the mean shift filtering process, the filtered data at the location (spatial location) of \( x_j \) will have the range components of \( y_{conv} \) (convergence point). The number of \( S_1(y_k) \) (windows) of radius 1 and centred on \( Y_k \) is \( n_k \). The unit radius of the windows is due to normalization.

### Mean Shift Segmentation Algorithm

1. For each \( j = 1 \ldots n \) run the mean shift procedure for \( x_j \) and store the convergence point in \( x_j \).
2. Identify cluster \( \{C_p\}_{p=1}^{m} \) of convergence points by linking together all \( z_j \) which are closer than 0.5 from each other in the joint domain.
3. For each \( j = 1 \ldots n \) assign \( L_j = \{p|z_j \in C_p\} \).
4. Optional: Eliminate spatial regions smaller than \( M \) pixels.

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**Figure 2. Mean Shift Segmentation Algorithm (written in pseudocode)**
Mean Shift Filtering Algorithm

1. Initialize \( k = 1 \) and \( y_k = x_j \)
2. Compute \( y_{k+1} = \frac{1}{n_k} \sum_{x \in S_k(y_k)} x_i k \leftarrow k + 1 \) till convergence
3. Assign \( x_j = (x_j^f, y_{comp}) \)

\[ \]

Figure 3. Mean Shift Filtering Algorithm (written in pseudocode)

6.5. Corner Detection

The cornerity index method is basically used to detect the corner of a given boundary shape. Let the sequence of \( n \) digital points describe a closed boundary curve (refer to equation 13).

\[
c = \{(x_i, y_i), \forall i = 1, 2, \ldots, n\}
\]

where \( p_i \) is a neighbour of \( p_{(i+1)mod_n} \) and \( (x_i, y_i) \) are the Cartesian coordinates of \( p_i \). Let \( S_k(p_i) \), for some integer \( k > 0 \), denote a small curve segment (c), the middle point \( (p_i) \) can be called as the region that provides support for \( p_i \) (by referring to Figure 4).

\[ \]

Figure 4. Illustration of Segment of C Boundary

The determination of \( p_{ie} \) from segment \( S_k(p_i) \) can be described as equation (14).

\[
p_{ie} = (x_{ie}, y_{ie})
\]

where \( x_{ie} \) and \( y_{ie} \) (respective mean) can be determined as equation (15) and equation (16).

\[
x_{ie} = \frac{1}{2k+1} \sum_{j=i-k}^{i+k} x_j
\]

\[
y_{ie} = \frac{1}{2k+1} \sum_{j=i-k}^{i+k} y_j
\]

Finally, the cornerity index of every \( p_i \) can be estimated using the Euclidean distance (refer to equation 17) (note \( x_i \) and \( y_i \) is a coordinate points value for each \( p_i \)).

\[
d = \sqrt{(x_i - x_{ie})^2 + (y_i - y_{ie})^2}
\]

The larger the cornerity index point value, the stronger the evidence that the point is a corner. Below are the conditions that were used to determine whether the point is corner
or not (refer to equation 18) (where the range of $c_{re}$ is 0.1 to 1 and $c[i]$ is the cornerity index of the current point).

$$\quad (1 + c_{re}) * c[i - 1] < c[i] \ AND c[i] > (1 + c_{re}) * c[i + 1] \quad (18)$$

### 6.7. Feature Matching

When features interest information has been obtained, the next step is to integrate this information together with WLAN Localization information. The WLAN [35] will give Localization information within 10m accuracy in order to select possible hallways where users should be located. Additionally, it provides the estimated gross centre for regions to be tested; the matching system can also search radius estimate based on accuracy and some ideas useful horizontal visibility location system camera. The integration of two (2) different information will finally make correspondence between the image captured and the floor plan. The reason behind this is to reduce ambiguous cases and search space Localization information in the database. For the correspondence part, there are too many possible correspondence. For example, let’s say we want to match 10 points in an image captured with 32 points in a floor map, the possible corresponding matches between image and floor points may result in 4 billion possible four-point correspondences. In order to solve this issue, we prefer to use Random Sample Consensus (RANSAC) [38] that operates to select and optimize the hypotheses. In this part, we use minimal structural assumptions to generate the hypotheses for the RANSAC algorithm in order to fit lines in the image-space features, which produces left and right correspondence lines.

RANSAC Algorithm {
1. Selects $N$ data items as random
2. Estimates parameter $\hat{x}$
3. Finds how many data items (of $M$) fit the model with parameter vector $\hat{x}$ within a user given tolerance. Call this $K$.
4. If $K$ is big enough, accept it and exit with success.
5. Repeat step 1 until 4 (as $L$ times)
6. Algorithm will be exit with fail
}

**Figure 5. RANSAC Algorithm (written in pseudocode)**

Then, the algorithm chooses at random two (2) points from each line in the image captured that orders the points along the lines consistently. Larger distances between 2 points means more stable likely produce stable camera. The RANSAC algorithm can be described in Figure 5.

### 7. Experimental Results

We categorize our experiment in two (2) types; indoor positioning and outdoor positioning. These experiments were conducted at Universiti Teknologi Malaysia, Johor, Malaysia; specifically indoor positioning was conducted at the Faculty Computing building, and outdoor positioning at Lingkaran Ilmu road (see Figure 6). For the indoor positioning experiment, we required to collect the WLAN signal strength by walking along the blue path at two (2) different regions. In this part, we use a mobile device (model: HTC HD Mini, software: WiFiFoFum) to collect the data in four (4) orientations for each point. Additionally, five (5) sample corridor image (at each of green dot) were taken. Meanwhile, for outdoor positioning, the data collection was obtained by taking GPS coordinate points (using GPS Trimble device) along the red path. These collected
data (GPS coordinate and WLAN signal strength) will be stored in the database subsystem. Finally, the positioning accuracy result can be obtained by comparing the current positioning information with positioning information which is stored in the database subsystem. Below, we discuss in more detail the performance of the proposed approach.

![Figure 6. Experiment Area (see Red Path for Outdoor Positioning Experiment area and Blue Path for Indoor Experiment Area)](image)

### 7.1. Outdoor Localization

The measured x-y coordinates and the latitude and longitude of the reference points are shown in Table 1. We performed experiments in which the x-y coordinates of the current position obtained by clicking the mouse on the window were compared with those obtained from the outdoor Localization program 200 times and the results are summarized in Table 2. The results indicate that among the 200 experiments, on 11 occasions the error was less than 1 m, on 17 occasions the error was between 1 and 2 m, and so on. The average error was 4.875 m.

![Figure 7. GPS Trimble Used for Data Collection (Outdoor Localization)](image)
Table 1. x,y Coordinates, Latitude and Longitude of Reference Points

<table>
<thead>
<tr>
<th>Coordinates</th>
<th>GPS data</th>
</tr>
</thead>
<tbody>
<tr>
<td>X</td>
<td>Y</td>
</tr>
<tr>
<td>A</td>
<td>1842</td>
</tr>
<tr>
<td>B</td>
<td>2112</td>
</tr>
</tbody>
</table>

Table 2. Summary of the Results of the Outdoor Localization Experiments

<table>
<thead>
<tr>
<th>Error (m)</th>
<th>0–1</th>
<th>1–2</th>
<th>2–4</th>
<th>4–6</th>
<th>6–8</th>
<th>8–</th>
</tr>
</thead>
<tbody>
<tr>
<td>Occurrence</td>
<td>11</td>
<td>17</td>
<td>61</td>
<td>51</td>
<td>33</td>
<td>27</td>
</tr>
<tr>
<td>Probability (%)</td>
<td>5.5</td>
<td>8.5</td>
<td>30.5</td>
<td>25.5</td>
<td>16.5</td>
<td>13.5</td>
</tr>
</tbody>
</table>

Average Error = 4.875 m

7.2. Indoor Localization

A rapid solution to determining an accurate position has been reached. Although this experiment does not show the real situation, it is possible to analyse to what extent the number of interest points detected influences performance. Figure 8 shows the results where the feature detector does not locate all possible points, but where the distribution is sufficient to allow localization. The location determination shows that the lowest trial percentage “no solution” situation is at Location 3 and Location 5 (16.5%) (‘no solution’ refers to situations where the location information cannot be determined, and the lowest trial percentage means the method least suffering from poor lighting conditions). Location 1 and Location 4 (43.5%) were the second-best locations and finally, Location 2 (90%) was the third-best location. This figure also shows that the most accurate localization at Location 2 (0.5%) is 0–1.5m. The comparison of experimental positions between location are illustrated in Figure 9 (for Locations 1, Location 2 and Location 5), and Figure 10 (for Locations 3 and 4).

Figure 8. Localization Accuracy Histogram
8. Conclusion and Future Works

In this paper, an ERL system has been proposed. This ERL system is based on the integration of GPS, wireless LAN and a camera. During experiments, the proposed method has been evaluated in five (5) types of different locations (inside building) and Lingkaran Ilmu road (outside building). The result shows that our method can survive in
59.3% illumination environments (illumination error usually happens inside a building). Additionally, it can also achieve positioning accuracy around below 6m in 13.7% trial (inside building), and 4.875m outside a building. The change in illumination makes it impossible to detect all the micro-landmarks in a region. Thus, it makes most of the detected interest points look scattered. We believe that there are a number of reasons for this phenomenon, such as the positions of the interest points being too scattered (or too far from the actual true points), the number of detected interest points being greater than the number of micro-landmarks, and fewer true interest points and position. An example situation, presented in Figure 11 and Figure 12, quite often occurs as a result of poor lighting conditions.

Figure 11. Example of Situation of False Matching at Location 4

Figure 12. Example of Situation of False Matching at Location 2

However, this does depend on which points are scattered or missing; for example, if only points from one side of the hallway are detected, our system cannot produce a result from a set of co-linear points. In the example reported, although the feature detector does not locate all possible micro-landmarks, the distribution is sufficient to allow localization. It may be possible to achieve reasonable results with fewer points detected if we also make use of line constraints or can constrain the camera pose by other means (either from other sensors, by image analysis, or by assumption). In the proposed scheme, the detection algorithm may also detect false features. For this reason, our RANSAC algorithm does not require all the detected features to be matched to floor plan features. Although we have not produced quantitative measures, we have found from various examples that these distracter points are handled well as long as approximately 80% of the points detected are
true features. As future work, we will continue our experiment using this result and combine it with other localization methods in order to determine how far our approach can affect user target position in hallways. Besides that, we are also enthusiastic to use another intelligent feature detector which can help this situation by classifying the quality of detected features.

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References


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