Victim Localization and Assessment System for Emergency Responders

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Abstract: In minor to moderate natural and man-made disasters, such as earthquakes and fires, people may be trapped inside buildings and hurt by the disaster. Considering that trapped victims may be unconscious, there is a high demand by emergency responders to get information on the locations and physical statuses of trapped victims inside a building during a disaster. In this paper, a smartphone-based, in-building emergency response assistance system, named *iRescue*, is presented. The system is comprised of two subsystems: a Victim Positioning System (VPS) and a Victim Assessment System (VAS). The VPS uses the received signal strength indicator of Wi-Fi signals from multiple wireless access points with referencing a pre-established Wi-Fi fingerprinting map of a building. The VAS uses patterns obtained from measured 3D acceleration changes by status of a victim. A Naïve Bayes classifier is employed for both VPS and VAS: for localization in between the fingerprinting map and for recognition of activities to be used for status assessment. The performance of the VPS has been validated by a localization test on a complex building. The VAS has been validated by activity simulation test with five people and real-time monitoring of a person equipped with an activity recording device. **DOI:** 10.1061/(ASCE)CP.1943-5487.0000483.

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Introduction

Disasters around the world are bringing considerable damage to our society. Natural and man-made disasters, including earthquakes, typhoons, hurricanes, cyclones, fires, terrors, and chemical exposure, can destroy our society's infrastructure as well as cause a substantial number of casualties. In the case of natural disasters, such as the well-known Hurricane Katrina in 2005 and the Haiti earthquake in 2010, the affected victims and areas were sizeable so that the rescue required world-wide and long-term action. But the majority of natural disasters are minor to moderate. For example, 90% of all earthquakes that have occurred since 1990 had magnitudes in the range M2–M5 [United States Geological Survey (USGS) 2014]. These minor to moderate earthquakes may bring slight damage to a building and hurt people inside. In the case of man-made disasters, fire in a building is the most frequent disaster to occur. In the U.S., about 1.4 million fires are reported and they cause more than 20,000 casualties every year (FEMA 2014b). Though large disasters impact society more, small to moderate disasters are more frequent and likely to occur in our lives.

In the case of small-scale disasters, people are apt to get trapped inside buildings. For example, a moderate earthquake may collapse a wall or a column of the structure or knock over furniture like bookcases. Then, victims might be trapped in the building, and get injured or even die if they do not get help from outside to escape. De Bruycker et al. (1983) reported that for the 1980 Italy Earthquake, the casualty rate for trapped people was 80% while only 9% for the people who were not trapped. In the case of fires in a building, most victims die from smoke or toxic gases and not from burns (Hall 2004). Therefore, rapid rescue of people inside the building is the key to reducing casualties in the case of small to moderate disasters.

Currently, emergency responders search for victims by three methods during disasters: physical search, canine search, and electronic search (FEMA 2014a). In the physical void search used in most incidents, emergency responders make visual and vocal assessments to locate victims. This method does not require any specialized electronic equipment but potentially can miss unconscious victims. The method is restricted to areas in which the emergency responders can go safely and is thus highly affected by site conditions such as visibility, temperature, time of day, etc. To locate unconscious victims, a well-trained canine team can be effective. However, a canine search is still affected by accessibility of the site and capability of the canine team. Furthermore, the canines have to take a rest periodically (e.g., 20–30 min of search followed by 20–30 min of rest). In some cases, electronic listening devices are deployed in search and rescue missions. The devices are able to cover large area by picking up the acoustic noises and vibrations coming from the victims. Electronic searches also have limitations in detecting unconscious victims and difficulty in deployment and monitoring at the site.

Due to these limitations of existing systems, considerable demand has emerged for a system that provides emergency responders with accurate and intuitive information at a disaster site. The

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authors have visited the Illinois Fire Service Institute and asked what would most help responders. The biggest demand was for a device to localize and assess the victims rapidly regardless of their state of consciousness. There have been considerable efforts to develop the systems to localize people and assess their physical status inside a building, though many of which were developed for general purposes. As for an indoor localization system, the first trial was a radio frequency-based indoor-user localization system, named RADAR (Bahl and Padmanabhan 2000), and many researchers have pursed similar approaches for indoor localization (Hatami 2006; Zàruba et al. 2007). They have focused on the use of Wi-Fi signals, as these are available in most indoor environments recently (Van Haute et al. 2013). Many researchers have employed Wi-Fi-based localization to smartphones along with their increasing usage, which showed successful localization performance (Kothari et al. 2012; Link et al. 2011; Liu et al. 2012; Martin et al. 2010; Pei et al. 2012; Subbu et al. 2013; Yim 2013). As to the physical status assessment, there have been many studies to identify activities that can be used to interpret physical statuses. Recognition has been carried out based on the measurements using embedded sensors, and the most-used measurement has been acceleration (Ravi et al. 2005). Activity recognition techniques have been extended to utilize various embedded sensors in smartphones by many researchers (Bin Abdullah et al. 2012; Keally et al. 2011; Khan et al. 2010; Lee and Cho 2011; Weiss and Lockhart 2012; Yan et al. 2012). Though the systems showed good performance in localization and assessment of people inside buildings, their development has not been tailored for disaster situations, such as localization under some wireless access points (WAPs) damaged and recognition of activities to assess the victims' status during a disaster.

Recently, a few studies reported on the use of decent technologies for emergency response operations. Peña-Mora et al. (2010) developed an information-technology-based collaboration framework supporting civil engineering emergency response operations. In that framework, critical building information is sent to responders during a disaster through digital devices via a wireless and ad-hoc networks. Rantakokko et al. (2011) proposed a concept for an indoor localization system for emergency responders using multiple sensors, such as GPS, magnetometers, barometers, imaging sensors, ultrasonic sensors, etc. In their paper, the possible technologies for indoor localization were surveyed to help people who want to develop a system to support the emergency responders. Li et al. (2014) proposed an environment-aware beacon deployment algorithm to enhance the sequence-based localization of trapped victims in fire situations. With integration of building information modeling (BIM) and metaheuristics, the beacons are optimally distributed to locate people in the building during a fire. While these researches provided significant directions for improving current emergency response systems, they have not provided a prototype that is ready to be employed in real disaster situations.

Smartphones can potentially become the devices able to realize the framework for localizing and assessing the victims to improve the effectiveness of emergency response. Smartphones are currently carried by over half of all people in the United States (Kerr 2013), and by over half of mobile phone users worldwide, and these fractions are increasing rapidly. All smartphones have onboard computational capabilities, multimetric sensors (e.g., accelerometers, microphones, cameras, gyroscopes, and magnetic field sensors), and wireless communication modules (e.g., cellular networks, Wi-Fi, and Bluetooth). Therefore, by employing the framework and technologies for the localization and assessment of victims via smartphones, the emergency response can be very rapid and effective.

In this paper, a smartphone-based, in-building emergency response assistance system, named *iRescue* (Illini Rescue System), is presented. *iRescue* provides two pieces of core information demanded by emergency responders: location and status of victims. The system is comprised of two subsystems: a Victim Positioning System (VPS) and a Victim Assessment System (VAS). The VPS is developed for smartphones using existing WLAN-based indoor localization systems, which use the received signal strength indicator (RSSI) of Wi-Fi signals from multiple wireless access points (WAP) with reference to a preestablished Wi-Fi fingerprint map of a building. Localization is improved in this study by implementing a Naïve Bayes classifier for localization in between the measured points statistically and in disaster situation where some of the WAPs might not work properly. The VAS is designed to estimate the status of a victim using 3D acceleration measurements from the smartphone. Six features that can be distinguished from the measured acceleration profiles with minimal computation are selected and linked with basic activities (e.g., sitting, lying, walking, running, etc.) of the victim. A Naïve Bayes classifier is again employed to compare the features from the measured acceleration with training data stored on the smartphone. Victim status (i.e., highly ambulatory, ambulatory, nonambulatory, and unconscious) are inferred by the emergency responders from the continuously calculated activities. The location and status information calculated using VPS and VAS, respectively, may be transmitted to emergency responders using a portable WLAN (Wireless Local Area Network) temporarily built at the disaster site. The timely information obtained by *iRescue* and sent to the emergency responders is expected to significantly improve the rescue process in terms of accuracy, reliability, and safety.

Naïve Bayes Classifier

Pattern classification algorithms have been widely employed in both activity recognition and the indoor localization systems (Bin Abdullah et al. 2012; Khan et al. 2010; Lee and Cho 2011; Parnandi et al. 2010; Pei et al. 2012; Ravi et al. 2005). Among various algorithms, the K-nearest-neighbor (KNN) classifier and the Naïve Bayes classifier are the most widely used techniques due to their effectiveness and simplicity. The KNN classifier calculates the Euclidean distance between the test input and the labeled training samples, and the test input is classified into the most frequent class among k nearest training samples (Cover and Hart 1967). Though the KNN classifier is relatively simple, it can be computationally expensive for large training sets, mostly because of the need for calculating all distances between the test input and the entire raining set. This time-consuming process is not appropriate for the near-real-time estimation using streamed inputs. On the other hand, the Naïve Bayes classifier is a simple probabilistic classifier based on Bayes' theorem with a naïve independence assumption that each feature contributes independently to the probability that an input belongs to a class (Duda et al. 1999). Naïve Bayes classifier is based on assumption that all features are conditionally independent; however the classifier can be also used when the features have some dependencies (Rish 2001). The Naïve Bayes classifier is found to be very efficient in many complex real-world situations (Zhang 2004); the parameters for the Naïve Bayes classifier can be obtained by calculating the mean and variance of the training data. Once the required parameters are obtained, they are stored and later used to estimate the testing data with minimal computation. The Naïve Bayes classifier is efficient in terms of data storage and computing resources, while having a high success rate.

Therefore, the Naïve Bayes classifier is employed in this study for both VPS and VAS.

Consider the task of determining the status of a victim given measured data from smartphone sensors. In the language of pattern classification, victim status is termed the "class" and is designated as C; "features", denoted F, are specific characteristics extracted from the measured data. Assume that there are m classes (i.e., victim states) and n features (feature selection will be discussed further in subsequent sections). The Naïve Bayes classifier uses Bayes' theorem to determine the most likely class (victim status), given the features. The probability of a class C being c_i (i.e., the likelihood that the state of a victim is c_i) can be written as

$$P(C=c_i|F_1,\ldots,F_j,\ldots,F_n) = \frac{P(F_1,\ldots,F_j,\ldots,F_n|C=c_i)P(C=c_i)}{P(F_1,\ldots,F_j,\ldots,F_n)} \tag{1}$$

where F_j = jth feature variable. Using conditional probability, the numerator of Eq. (1) can be rewritten as

$$\begin{aligned}P(C=c_i)P(F_1,\ldots,F_j,\ldots,F_n|C=c_i)&=P(C=c_i)\\ \times P(F_1|C=c_i)P(F_2,\ldots,F_j,\ldots,F_n|C=c_i)&=P(C=c_i)\\ \times P(F_1|C=c_i)P(F_2|C=c_i,F_1),\ldots,P(F_n|C=c_i,F_1,F_2,\ldots,F_{n-1})&\end{aligned} \tag{2}$$

The Naïve Bayes rule follows the assumption that all features are conditionally independent to every other feature. Then the Eq. (2) can be written as

$$\begin{aligned}&P(C=c_i|F_1,\ldots,F_j,\ldots,F_n)\propto P(C=c_i,F_1,\ldots,F_n)\\ &\propto P(C=c_i)P(F_1|C=c_i)P(F_2|C=c_i),\ldots,P(F_n|C=c_i)\\ &\propto P(C=c_i)\prod_{j=1}^{n}P(F_j|C=c_i)\end{aligned} \tag{3}$$

$$P(C=c_i|F_1,\ldots,F_n)=\frac{1}{Z}P(C=c_i)\prod_{j=1}^{n}P(F_j|C=c_i) \tag{4}$$

where Z = denominator of Eq. (1), which can be neglected during the classification because the probability of the features can be assumed to be constant.

$P(F_j|C=c_i)$ where $j=1,\ldots,n$ can be obtained by assuming an underlying Gaussian probability distribution and using the training data to estimate the associated parameters. From the Bayes' rule, the estimated class will be the one that has the highest value in the product of the conditional probability of every feature, i.e.

$$c^* = \arg\max_{c_i} P(C=c_i)\prod_{j=1}^{n}P(F_j=f|C=c_i) \tag{5}$$

where c_i = classified class and f is the feature value of the test data.

The Naïve Bayes classifier outlined in this section will be used for both the VPS and VAS modules to classify the location and status of the victim. First, the training data will be used to determine the parameters for the Gaussian probability $P(F_j|C=c_i)$; subsequently, using the Bayes' Theory and by assuming statistical independence of all features, $P(C=c_i|F_1,\ldots,F_n)$ will be calculated using Eq. (4). Finally the state will be classified as the one that has the maximum probability shown as Eq. (6). This approach will provide the expected location (for VPS) and status (for VAS) of the victim.

Development of the Victim Positioning System

The VPS relies on Wi-Fi signals from wireless access points (WAPs) to find the locations of smartphones inside a building following a disaster. Many buildings, both residential and commercial, have several WAPs that can be leveraged for the tracking of indoor locations. The VPS is developed on top of the assumption that everyone in the building has Wi-Fi-enabled smartphone and the number of detectable WAPs is three or more anywhere inside the building. It is further assumed that many of these WAPs will survive a minor to moderate disaster and continue working.

The VPS is developed upon the well-known WLAN-based indoor localization system called RADAR. RADAR uses the presence of WAPs in addition to the received signal strength indicators (RSSI) of the detected WAPs in the building to estimate a location. The estimation is based on the fingerprinting map, which is a process of recording the RSSI together with the unique ID of each detectable WAP and the corresponding location inside the building. Finally, the K-nearest neighbor search algorithm is used to estimate locations.

In this study, to take account for disaster scenarios, where there are more uncertainties in the RSSI values, the modified Naïve Bayes classifier is adopted instead of the K-nearest neighbor to provide the location based on the fingerprinting data. Referring to the VPS flowchart shown in Fig. 1, the RSSI signal is first collected by the smartphone, along with the Basic Service Set Identification (BSSID) which is the unique ID for each WAP. Appropriate features are then obtained by reading the RSSI. Finally, the Naïve Bayes classifier is applied to the features to estimate the most likely location of the victim. To consider the scenario where some WAPs are not detected due to the disaster, the Naïve Bayes classifier was modified to consider only the features that are detected. Location information can be displayed locally on the smartphone as part of a system to guide the victim to the nearest safe exit, and can be transmitted for use by the on-site emergency responders.

Wi-Fi Received Signal Strength Indicator

Wi-Fi RSSI is one of the popular indicators used for indoor localization. The RSSI is a measurement of the power present in a radio signal received by the antenna. Assuming the WAP radiates a consistent Wi-Fi signal in free space without any obstacles, the RSSI is expected to be proportional to the inverse of the square of distance to the WAP. However, in reality, the radiated Wi-Fi signal can be

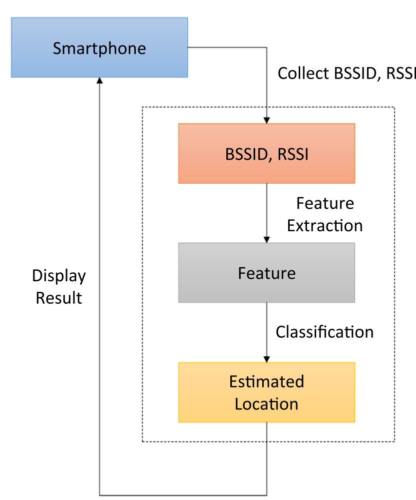


Fig. 1. Flowchart of VPS

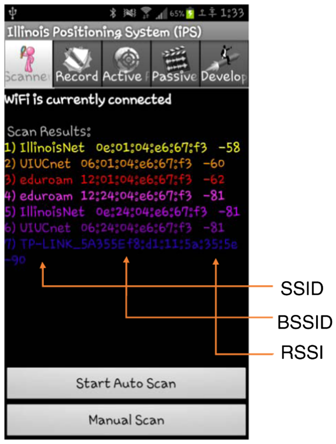


Fig. 2. Screenshot for Wi-Fi RSSI scanner

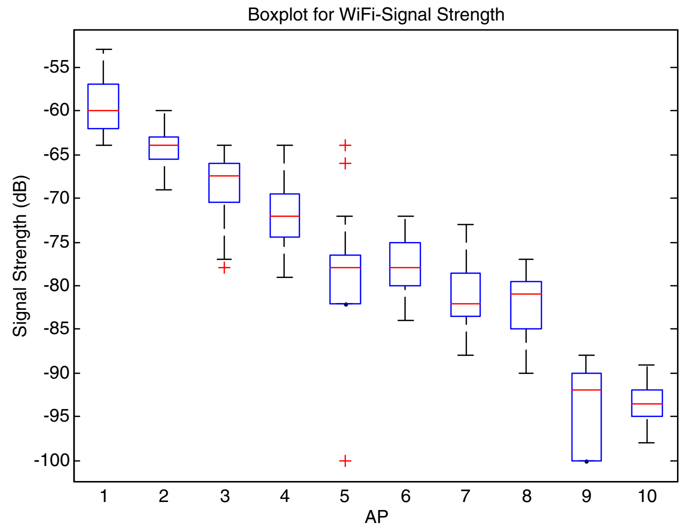


Fig. 3. Box-and-Whisker plot illustrating RSSI variability over a 100 s recording epoch for 10 different wireless access points detectable from a single location

reflected or refracted by fixed and moving objects (e.g., walls and people) and consequentially can exhibit spatial and temporal instability. This uncertainty prevents the direct use of trilateration technique to localize the phone by taking RSSIs from multiple APs (Mok and Retscher 2007).

Wi-Fi RSSI Scanner

To capture the RSSI of multiple WAPs, a Wi-Fi RSSI scanner module was developed and deployed on the Android OS smartphone platform, as shown in Fig. 2. Scanning the WAPs does not require a connection to be made, but only to record the Service Set Identification (SSID), the Basic Service Set Identification (BSSID), and the corresponding RSSI for each detected WAP. SSID is the name of the Wi-Fi network, and BSSID is the Media Access Control (MAC) address of the WAP, which is a unique identifier representing each WAP. Different colors are used to make each detected WAP distinguishable.

Characterization of RSSI Variability

At a fixed location in a building, the RSSI levels detected by a smartphone may vary over time depending on several factors. If this variability is too large, it may negatively impact localization performance. We performed two experiments to assess RSSI variability in order to better understand the implications for our localization algorithm.

Effect of Phone Direction

One important factor influencing the RSSI level is the positioning of the user's body relative to the phone and WAP signal source, as the high water content in the human body attenuates or "shadows" the Wi-Fi signal (Bahl and Padmanabhan 2000). To characterize this effect, a test was conducted in a large room with a single WAP located at the center. At three difference distances from the WAP (i.e., 1, 3, and 5 m), the RSSI was measured with the user holding the phone facing directly towards or directly away from the WAP. Table 1 shows the average RSSI values for 10 measurements obtained from the test. Facing toward the WAP resulted in larger average RSSI values than when the user was facing away from the WAP for all three distances. The result shows that the user's body shadows the Wi-Fi signal, and the attenuation is greater closer to the WAP. This effect of user body on the received signal strength is even more significant when the initial received signal strength from the WAP is weaker. This test indicates that the orientation of the user should be considered in the fingerprinting process to improve the accuracy of localization.

RSSI Stability

Even with a fixed user orientation, the RSSI levels measured by a phone at a fixed location were found to be variable over time. To characterize the real-world variations in the RSSI, a test was carried out in a college building with many students passing in the vicinity. The RSSI values for 10 detectable WAPs were measured at a specific location with a 0.1 Hz sampling rate for 100 s. Fig. 3 is a box-and-whisker plot (Tukey 1977) of the measured RSSIs for the 10 WAPs. The box-and-whisker plot shows the median and the variation of the RSSI for each AP. On each box, the center mark is the median, the edges of the box are the 25th and 75th percentiles, the whiskers extend to the most extreme data points except outliers, and outliers are plotted with "+" marks individually. In these tests, the temporal fluctuation in the RSSI was usually within the range of about 5 dB. Because, in most buildings, the RSSI value in different rooms varies by around 10 dB, the RSSI signal can still be used for localization even with the temporal variation of 5 dB. This variation can be decreased by temporal

Table 1. Effects of Body Shadowing on the Measured RSSI (Higher Values Represent More Powerful Signals)

Distance	1 m		3 m		5 m	
Direction	Facing towards	Facing away	Facing towards	Facing away	Facing towards	Facing away
Average RSSI (dB)	−32.9	−44.4	−36.7	−41	−49.7	−53.8
STD	1.22	3.26	1.84	1.10	1.10	2.68
Diff (dB)	−11.5		−4.3		−4.1	

averaging, which is used in construction of the feature set for the Naive Bayes classifier, described in "Naïve Bayes Classifier" Section.

Localization Using RSSI

Before the fingerprinting step, a feature is developed from the measured RSSI values to localize the phone with improved accuracy. Two kinds of modifications were included in the development. Firstly, the temporal variation of the measured RSSI, which was shown in Fig. 3, is minimized by taking average of the RSSI values. The RSSI scanner module can sample the RSSI every 0.1 s, and the average of 10 consecutive RSSI values, measured for 1 s, is considered as the representative RSSI at a location. Secondly, undetected WAPs are assigned a default RSSI value of $-100\,\mathrm{dB}$, which is the smallest value that an Android system can reliably detect.

Therefore, the RSSI feature is defined as

$$F_i = \begin{cases} \overline{\mathrm{RSSI}}_i & \text{if } \overline{\mathrm{RSSI}}_i \geq -100\text{ dB} \\ -100 & \text{if } \overline{\mathrm{RSSI}}_i < -100\text{ dB or WAP}_i \text{ is not detected} \end{cases} \tag{6}$$

where $\overline{\mathrm{RSSI}}_i$ = average of 10 consecutive RSSI values from the WAP_i.

Fingerprinting Using Naïve Bayes Classifier

The fingerprinting is a process of developing a signal strength map using unique tags of WAPs for densely distributed locations in a building. This fingerprinting procedure is enabled by the Naïve Based Classifier based on the localization feature shown in Eq. (6). The goal is to reach room-level accuracy. For a specific room, the localization features are obtained at eight locations with different phone orientations as shown in Fig. 4. Several measurements are carried out to build the conditional probability by the Naïve Bayes classifier.

The Naïve Bayes Classifier works based on the assumption that the features used in the Classifier have the probability pattern of normal distribution. Under the regular operation conditions, the RSSI usually follows the normal distribution (Bose and Foh 2007; Zanca et al. 2008). However, there are some researches showing that the RSSI values are not normally distributed, but rather skewed (Kaemarungsi and Krishnamurthy 2004; Ladd et al. 2005). In the literature, the skew is caused by user interference. Thus, the Naïve Bayes Classifier is can be used effectively if the direction effect is also included in the fingerprint mapping process.

The conditional probability for certain feature F_i having RSSI_i from the location l_j can be calculated from the probability density function (PDF) constructed using the collected RSSI data (i.e., fingerprinted data). The distribution of RSSI for each WAP when the device is in certain room was assumed as being a Normal Distribution as follows:

$$P(F_i|L = l_j) = \frac{1}{\sigma_{j,i}\sqrt{2\pi}} e^{-(f_i-\mu_{j,i})^2/2\sigma_{j,i}^2} \tag{7}$$

If a signal is consistent for a certain location, the fingerprinting map can be constructed using a single measurement at each location. However, as stated in the previous section, the Wi-Fi RSSI has uncertainty due to temporal instability and the direction effect. To minimize temporal instability, the measurement was taken several times in different time periods. In order to take account for the directionality issue, fingerprinting was done for eight different directions for each room as Fig. 4. Each room r will contain eight location ID (l) for each direction. [e.g., $r_j = (l_{8j-7}, l_{8j-6}, \ldots, l_{8j})$]

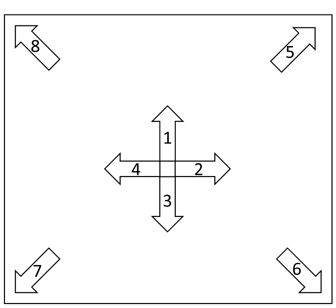


Fig. 4. Fingerprinting of room level considering phone direction effect

Maximum Likelihood Method with Selective Features

Finally, the unknown location can be estimated by using the Maximum Likelihood Method shown in Eq. (6). However, unlikely to the original Naïve Bayes classifier, the number of features detected in a room can be different from those detected in another room. This problem was resolved in the fingerprinting stage by setting the threshold values for features that has not been detected. However, when calculating the maximum likelihood, this approach will not only increase the calculation cost, but also decrease the accuracy. Especially, in emergency situation, some RSSI values might be undetected because of damaged or unpowered WAPs. Therefore the original classifier was modified to consider only the features that have appeared in the test data and will be considered as in the following equation. The prior probability $P(R = r)$ was considered as a constant value without any additional information, and thus was neglected.

$$\mathrm{Classify}(F_1', \ldots, F_m') = \arg\max_r \prod_{i=1}^{m} P(F_i'|R) \tag{8}$$

where F_i' = renumbered feature for the detected WAPs only, and m = number of the detected WAPs.

Development of the Victim Assessment System

Configuration of the Victim Assessment System

The Victim Assessment System (VAS) is designed to assess and inform the emergency responders of the status of the victims along with their locations estimated by the VPS. The information is necessary to prepare evacuation plans and determine the appropriate treatment of victims. The easiest and most accurate way to check the status of victims is communicating directly with them, in the same way a doctor asks a patient about his or her condition. However, in disaster situations, phone lines may be down due to either physical damage to infrastructure or network congestion. Even if the phone lines and internet network are available, emergency responders may not be able to communicate directly with all potential victims to determine their status in a reasonable amount of time. To communicate with victims more efficiently, the VAS is comprised of two subsystems that use the local network that is assumed to survive in the disaster, or which can be established postdisaster by deploying an area of WAPS around the disaster site: (1) an Active Victim Assessment System (AVAS), a subsystem collecting useful information from conscious victims by questionnaires, and (2) a Passive Victim Assessment System

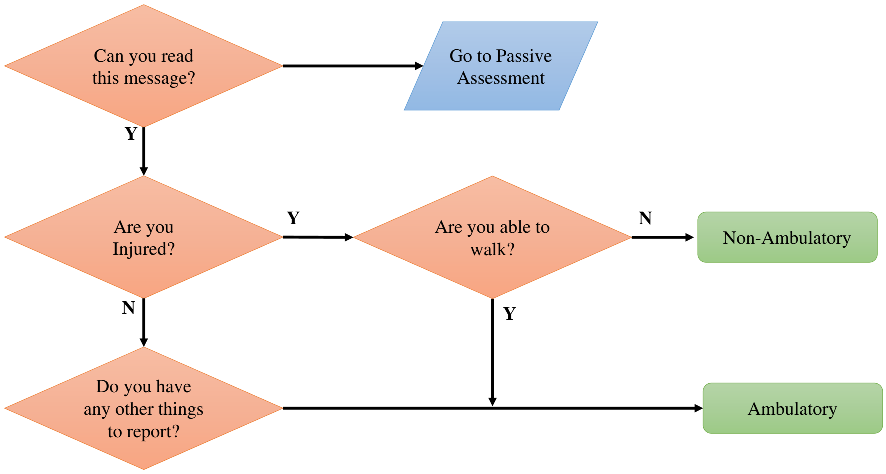


Fig. 5. Flowchart with example questions to determine victim status using AVAS

(PVAS), a subsystem continuously monitoring victims by using sensors inside their smartphone. AVAS will send questions directly to the victims, and PVAS will estimate the status of those who are not able to, or fail to respond to, the queries from the AVAS (Fig. 5).

Active Victim Assessment System

AVAS asks simple questions on the physical status of the victims inside a building via smartphones. The questions can be selected by the emergency responders according to the types of disaster and emergency. The question can be answered simply by selecting either a "yes" or "no" button so that even injured victims could easily report their current situation to emergency responders. Fig. 5 shows example questions from the AVAS. AVAS will determine whether the victims are ambulatory or nonambulatory based on the answers to the questionnaires. Furthermore, AVAS will collect useful information that the victims want to report via a voice message. All of this information will be aggregated and made available to emergency responders on a timely basis.

Passive Victim Assessment System

PVAS assesses the status of victim in an automated manner by collecting real-time data from sensors, such as an accelerometer, a gyroscope, and a magnetic field sensor embedded in the smartphone. PVAS is developed for the victims who are unconscious by injury and who are not aware of this application running in their smartphones, and it is enabled automatically if no response is collected by the AVAS as shown in Fig. 6. PVAS recognizes eight different types of activities (walking, running, standing, sitting/lying, rolling, fainting, stepping up stairs, and stepping down stairs) using the Naïve Bayes classifier with periodic updating. Estimated activities could be further linked into the four physical statuses of victims (highly ambulatory, ambulatory, nonambulatory and unconscious) in order to aid emergency responders in coordinating evacuation and rescue efforts. Fig. 6 shows the flowchart of determining the status of the victim by PVAS. For best results, victims must have their smartphones in their pocket, not in their bag, to capture the responses of the victims themselves. The remaining part of this section describes how the PVAS works automatically in a disaster.

Data Collection and Preprocessing

Sensor Data Scanner

To find the best features that can assess a victim's status using the sensor data experimentally, a sensor data scanner module is

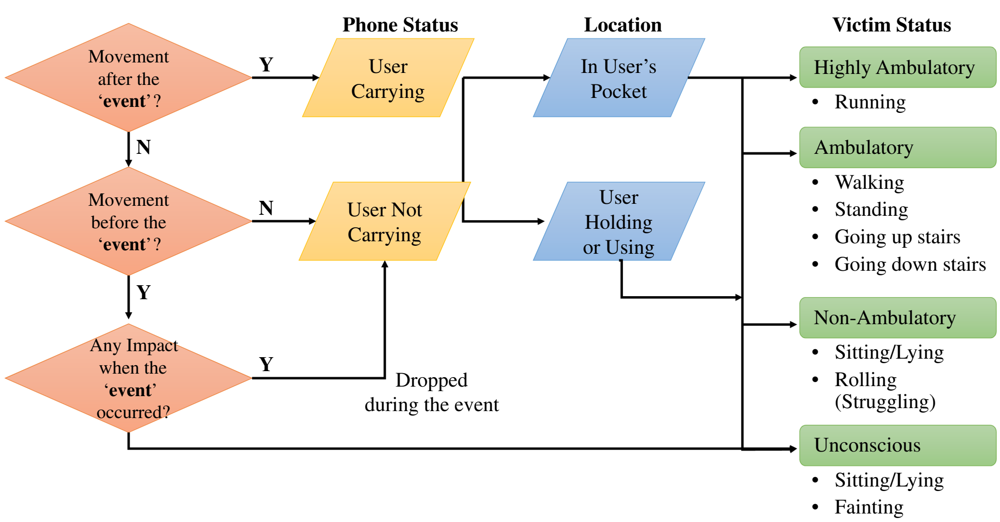


Fig. 6. Flowchart for determining the status using PVAS

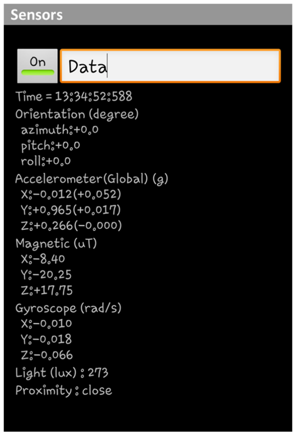


Fig. 7. Screenshot for sensor data scanner

developed on the Android OS and embedded in the PVAS, as shown in Fig. 7. The types of measurements and sampling frequency are adjustable by the user; 3-axis acceleration and 3-axis magnetic field data are collected at the rate of 10 Hz in this study. The orientation of the phone, calculated by the Android OS, is also displayed. The measurement can be exported into a text file for further development of the software.

Transforming Acceleration Sensor Data into Global Coordinate System

The acceleration data of the phone is originally collected in the phone's local coordinate system shown in Fig. 8. The local coordinate system in the Android OS defines the x-axis as horizontal, y-axis as vertical, and z-axis as perpendicular to the phone, and the global coordinate system defines the X-axis as west, Y-axis as north, and the Z-axis as toward the center on the Earth. The acceleration in the local coordinate system (e.g., a_x, a_y, and a_z) varies according to the phone's orientation, and it needs to be transformed into the global coordinate system (e.g., a_X, a_Y, and a_Z) that is invariant to the orientation of the phone.

In this study, the transformation is made using the 3D transformation matrix (T) composed of three well-known Euler angles: roll (θ_x), pitch (θ_y), and yaw (θ_z) (Diebel 2006). The angles around the local axes can be obtained using two conditions: (1) according to the global coordinate system shown in Fig. 8, the global acceleration will have zero values for X and Y directions and constant of gravitation (i.e., 1 g) for the Z direction when there is no external

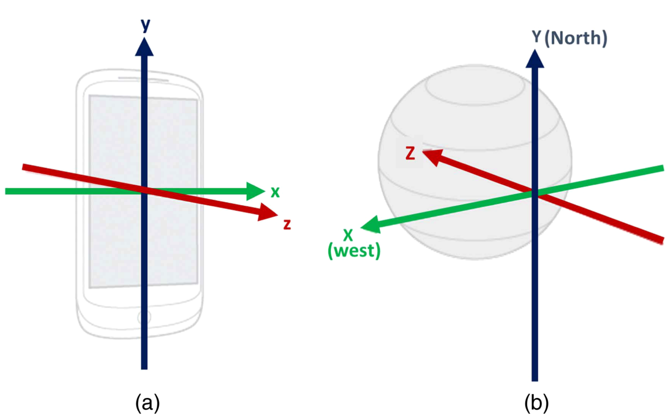


Fig. 8. (a) Local coordinate system; (b) global coordinate systems

acceleration other than gravitation, and (2) the global magnetic field directed from south to north will always have a zero value for X direction heading west. Then, the transformation matrix T can be obtained from

$$\begin{bmatrix} 0 \\ 0 \\ g \end{bmatrix} = T \begin{bmatrix} a_x \\ a_y \\ a_z \end{bmatrix} \tag{9}$$

$$\begin{bmatrix} 0 \\ m_Y \\ m_Z \end{bmatrix} = T \begin{bmatrix} m_x \\ m_y \\ m_z \end{bmatrix} \tag{10}$$

where a and m denote the measured acceleration and magnetic field, respectively; and their small and large subscripts denote the local and global coordinate systems, respectively. Then, the global acceleration can be obtained using the transformation matrix as

$$\begin{bmatrix} a_X \\ a_Y \\ a_Z \end{bmatrix} = T \begin{bmatrix} a_z \\ a_y \\ a_z \end{bmatrix} \tag{11}$$

When θ_y is 90°, i.e., $\cos\theta_y = 0$, the Gimbal lock problem may occur (King 1998). Quaternions may provide the solution to avoid the problem (Kuipers 1999).

Even though the coordinate transformation of the sensor data from the device coordinates into global coordinates has been introduced, the system still relies upon the assumption that the smartphone is in use (Active VAS) or in the pocket (Passive VAS). These two components of the VAS will cover a substantial portion of the victims trapped in the building, but those who do not have their smartphones with them or who keep their phones in their bags or purses will not receive the full benefit of the system. The system can be expanded to more general cases by using wearable devices such as smart watches and glasses so that more people can get the benefit of the system in the future.

Features for Victim's Status

Proper processing of acceleration data yields the features that can assess the status of victims using the pattern classification methods, such as Naïve Bayes classifier. In this study, six distinguishable features are selected to identify eight activities based on the intuitive understanding of human activities as summarized in Table 2. The features are extracted from the acceleration in the global coordinate system and magnetic field. The absolute vertical and horizontal acceleration ($\boldsymbol{F}_1$ and $\boldsymbol{F}_2$) distinguish movements with vigorous vertical (e.g., running, walking) and horizontal (e.g., running, walking, rolling) vibration from static movements, respectively. The movements that are more likely to be horizontal (e.g., rolling) can be distinguished using the ratio between the vertical and horizontal acceleration level ($\boldsymbol{F}_3$). The variance of the velocity ($\boldsymbol{F}_4$) distinguishes movements with high variance (e.g., fainting) from low variance (e.g., standing). The stationary movement with high frequency (e.g., running) can be distinguish with movement with low frequency (e.g., walking) by dominant frequency ($\boldsymbol{F}_5$). Finally the orientation of the phone ($\boldsymbol{F}_6$) can distinguish whether the phone is in parallel position (i.e., laying/sitting) to the floor or perpendicular (e.g., standing).

The flowchart for the feature extraction is shown in Fig. 9. The direct current (DC) offset of acceleration, assumed to correspond to the gravitation, is calculated, and the orientation of the phone is calculated using the DC offset and magnetic field data.

Table 2. Features for PVAS

Feature	Mathematical expression	Distinguishable activities		
		Large	Moderate	Small
F_1	$\sqrt{E(a_Z^2)}$	Running	Walking	Standing, lying/sitting
F_2	$\sqrt{E(a_X^2 + a_Y^2)}$	Rolling	Running, walking	Standing, lying/sitting
F_3	$\sqrt{E(a_Z^2)}/\sqrt{E(a_X^2 + a_Y^2)}$	Fainting	Running, walking	Rolling
F_4	$\mathrm{Var}(v_Z)$	Fainting	Running, walking	Standing, lying/sitting
F_5	$\arg\max_f[\mathrm{F}(a_Z)]$	Running	—	Walking
F_6	$\mathrm{abs}(\theta_X + \theta_Y)$	Standing	—	Lying/sitting

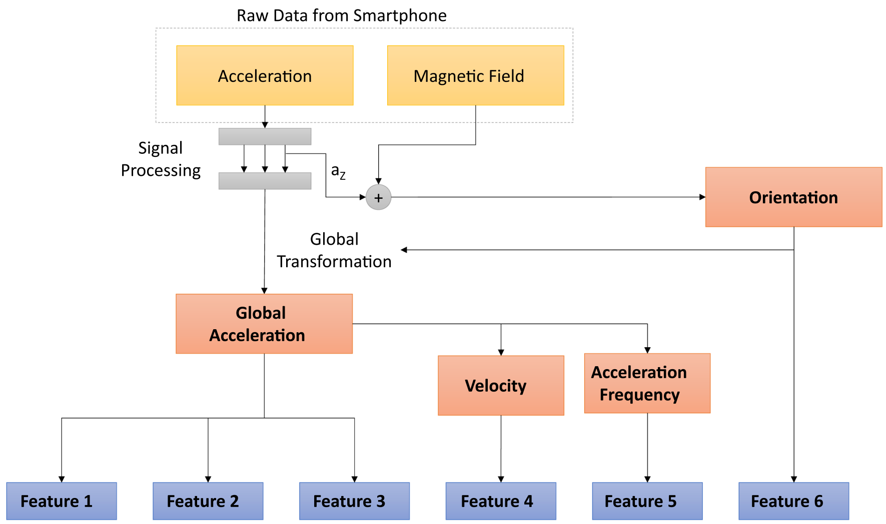


Fig. 9. Flowchart for feature extraction from sensor data

The acceleration data in the local coordinate system after removing the DC offsets, is then transformed into the global coordinate system using the estimated orientation. The features $\boldsymbol{F}_1 \sim \boldsymbol{F}_4$ are calculated from the global acceleration, and $\boldsymbol{F}_5$ is obtained from the Fourier spectrum of measured acceleration. F_6 contains two components (i.e., pitch and roll) of the phone. The Fourier spectrum is calculated using 64 pieces of acceleration data so that $\boldsymbol{F}_5$ is updated every 6.4 s. The other features are also updated every 6.4 s.

Status Assessment Using the Naïve Bayes Classifier

After getting these features, the activities of the victim are obtained using the Naïve Bayes classifier; these activities can be used to infer the status of the victim. The probability of a dataset having features $F_1, F_2, \ldots, F_n$ being class C_i can be calculated with Eq. (4). The success rate of the classification by the Naïve Bayes classifier significantly depends on the type of the probability density function of the features. To select the appropriate distribution for each feature, a normality test was done for the features obtained from the sampled measurements with each activity. Fig. 10 shows the example normal and log-normal probability plots of F_1. The "+" symbol indicates the sample data is plotted with the dashed line indicating robust linear fit of the sample. If the sample data fits into the distribution exactly, the blue "+" symbols will show linear line. The other features F_2–F_6 also showed similar pattern that follows the log-normal distribution, though they are not shown in this paper. While the normal distribution was used to represent the features for VPS (e.g., RSSI), the features for PVAS, on the other hand, does not follow the normal distribution. The result indicates that the features in PVAS are better represented by a log-normal distribution. Therefore the conditional probability for certain feature F_i for activity status s_j can be calculated from the PDF constructed by Log-Normal Distribution as follows:

$$P(F_i|S = s_j) = \frac{1}{\sigma_{j,i}\sqrt{2\pi}} e^{-(\log f_i - \mu_{j,i})^2/2\sigma_{j,i}^2} \tag{12}$$

Integrated Victim Rescue System: *iRescue*

iRescue, an Android-based victim rescue system, was developed by integrating the two explained systems, VPS and VAS, as shown in Fig. 11. The current version of *iRescue* has three tabs to verify the performance of the proposed VPS and VAS. The VPS tab [Fig. 11(b)] estimates the current location of the user and shows the location on a map. The AVAS tab [Fig. 11(c)] asks questions directly to the user to get their responses. The PVAS tab [Fig. 11(d)] estimates the status of the victim and visualizes the results on the phone. All of these pieces of information (the estimated location and status of the victim) will be transmitted to the emergency responders in real time via TCP-IP protocol using a local network. The current version of application does not have the ability to be installed and launched automatically when an emergency occurs. However, if the proposed system is adopted for practical use, this issue can be potentially solved by recommending wireless carriers pre-install the application prior to activation. Thus, when an emergency occurs, it is assumed that the application can be launched remotely by emergency responders.

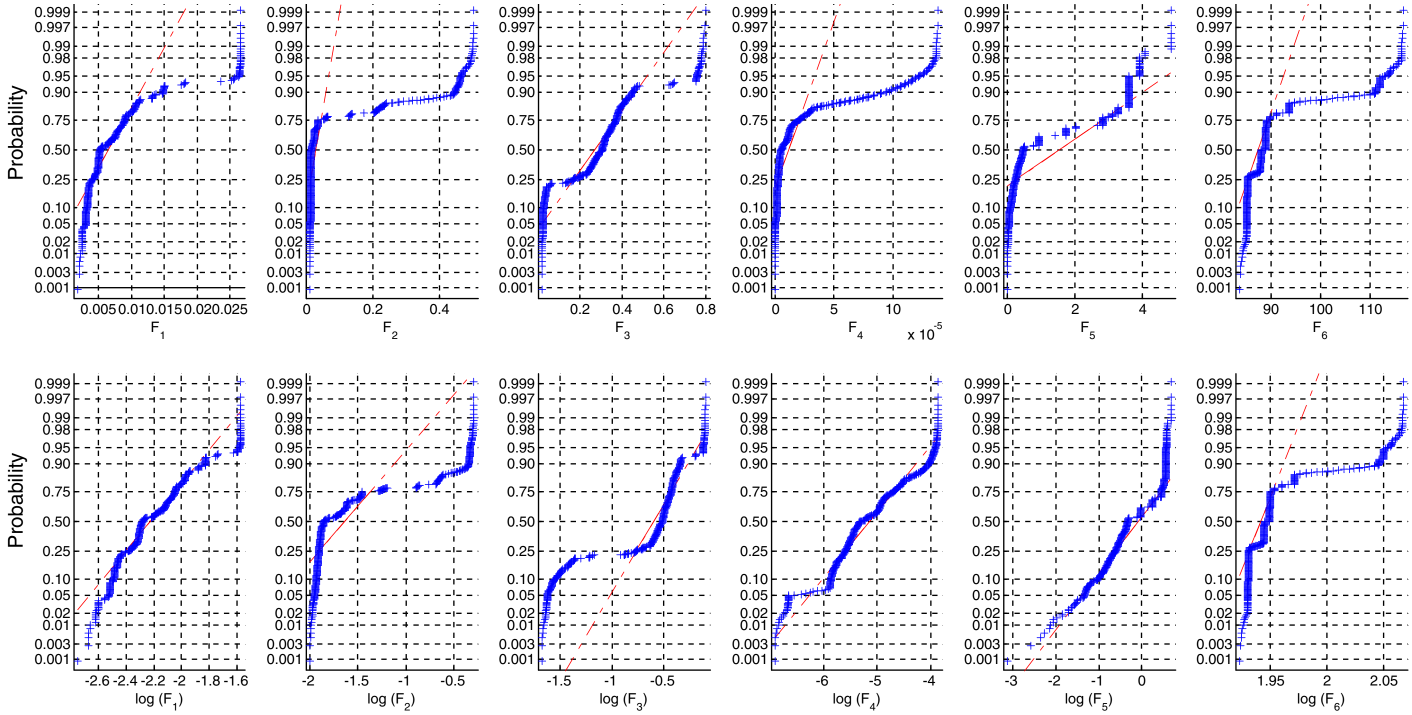


Fig. 10. Probability plot for features 1 ~ 6 (top: normal, bottom: log-normal)

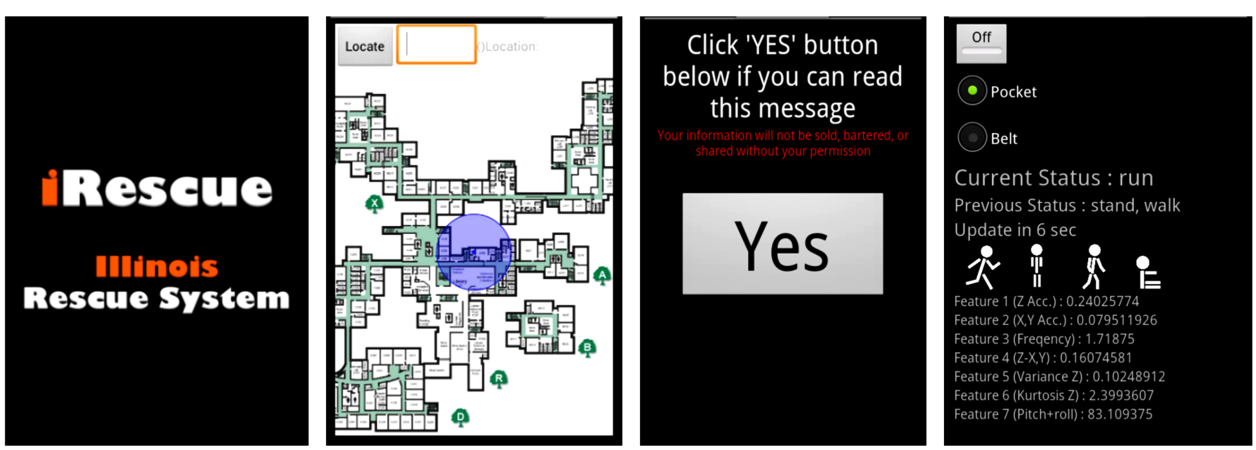
VPS calculates the probability of being in a certain location (Fig. 12 left) and shows the location with the highest probability together with floor map that has a touch interface (Fig. 12 right). The estimated location will be shown in the top when pressing the locate button in the top left corner. It will also indicate the current location in the map using the blue circle. VAS calculates the probabilities of victims having a certain status (Fig. 13) and shows the activity having highest probability within every 6.4 s. Also, the recent activity history will be displayed by images that could be used to determined status of the user.

System Validation

The performance of *iRescue* for the localization and assessment of victims in a building has been investigated via a series of validation tests. In this paper, the validation tests for the VPS and VAS have been carried out separately. The validation test of the VPS was carried out at the 2nd floor of Wing B of Parkland College, located in Champaign, Illinois. The validation of the VAS was carried out in two ways: activity simulation in a building with five people and real-time monitoring of a person equipped with various devices recording his activities. The smartphone used in the validation tests is a basic "HTC Nexus One" (HTC, New Taipei, Taiwan).

Validation Test: Victim Positioning System

The validation test of the developed VPS was conducted on the 2nd floor of Wing B of Parkland College, located in Champaign, Illinois. The map of the test area is shown at Fig. 14. The test area has 9 rooms and 34 detectable WAPs around the floor. For the validation, the RSSIs from the WAPs were collected for eight different



(a) (b) (c) (d)

Fig. 11. Screenshots for *iRescue*: (a) startup screen; (b) VPS; (c) AVAS; (d) PVAS

(a) (b)

Fig. 12. (a) P-values of VPS for sample data at B226; (b) final result for VPS

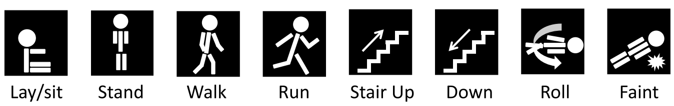


Fig. 13. Activities for VAS

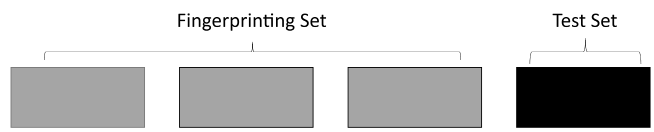
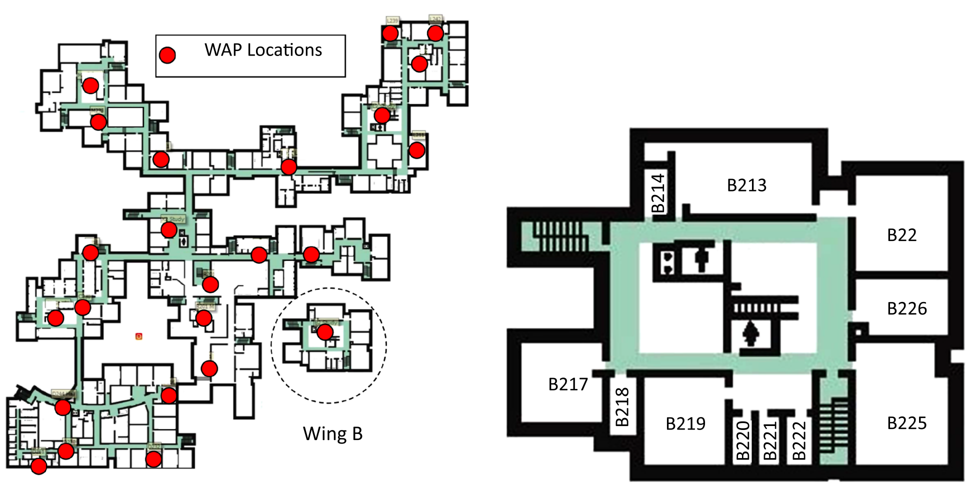


Fig. 15. 4-fold cross validation

directions, shown in Fig. 4. A 4-fold cross validation method was employed, which uses 1/4 of the data for testing and the other 3/4 as training (i.e., fingerprinting), as shown in Fig. 15. Because the positioning does not depend on people's activity patterns, all data were collected by a single person. The data were collected 30 times in 3 weeks to check for temporal variations in the building environment.

Result Comparison for Naïve Bayes and Modified Naïve Bays Classifier

The average success rate for using original Naïve Bayes classifier was about 72% in room-level accuracy while the Modified NB that considers only the features that appeared, was about 79%. The modified method can increase the classification accuracy by 7% compared to the original Naïve Bayes classifier (Fig. 16).



(a) (b)

Fig. 14. Floor plan and location of WAPs for (a) 2nd floor of Parkland College; (b) for Wing B

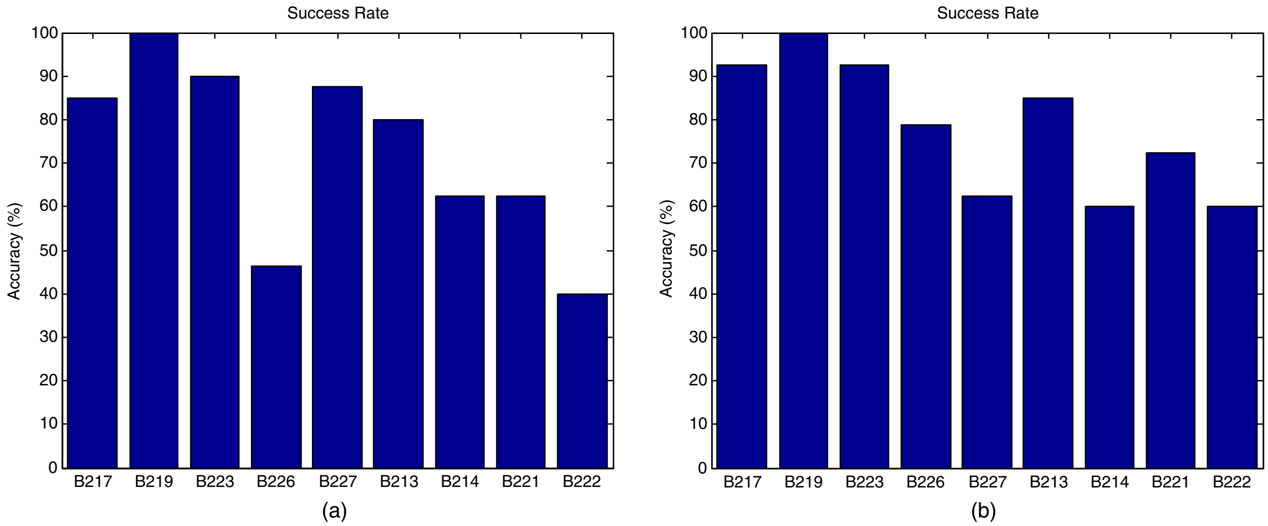


Fig. 16. Success rate for (a) using Naïve Bayes classifier; (b) using modified Naïve Bayes classifier

Table 3. Confusion Matrix without Considering Directionality Effect

Actual room	Localized room 217	219	223	226	227	213	214	221	222
217	**0.93**	0.07	0.00	0.00	0.00	0.00	0.00	0.00	0.00
219	0.00	**1.00**	0.00	0.00	0.00	0.00	0.00	0.00	0.00
223	0.00	0.00	**0.93**	0.07	0.00	0.00	0.00	0.00	0.00
226	0.00	0.00	0.00	**0.79**	0.21	0.00	0.00	0.00	0.00
227	0.00	0.00	0.00	0.37	**0.63**	0.00	0.00	0.00	0.00
213	0.00	0.00	0.00	0.00	0.00	**0.85**	0.15	0.00	0.00
214	0.00	0.00	0.00	0.00	0.00	0.40	**0.60**	0.00	0.00
221	0.00	0.24	0.00	0.00	0.00	0.00	0.00	**0.73**	0.03
222	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.40	**0.60**

Note: Boldface indicates classes classified correctly.

Result Comparison for with and without Directionality Effect

Table 3 is a confusion matrix (Kohavi and Provost 1998) for the case without considering the directionality effect. Locations for eight different directions were labeled as all different classes for the data for the test considering the directionality effect, while locations in the same room were all labeled as same class for the test without considering directionality. Each column of the confusion matrix represents the instances in a predicted class, while each row represents the instances in an actual class. Because the directionality of the device can have different RSSI values for certain WAPs, the classifier incorrectly identified some locations. For example, the RSSI from some WAPs for room B214 were more likely to be those of the next door which is B213, which led to this misclassification.

Fig. 17 shows the classification result with and without considering the directionality effect. When considering the directionality, data obtained from different directions (Fig. 4) in a single room was considered as different classes. In contrast, all of the directions in a single room were considered as a single class for the latter case. When directionality was considered, some of the misclassification that was made as shown in Table 3 was removed, which eventually increased the accuracy into 87%.

Victim Assessment System Validation

Two validation tests were conducted to verify the performance of the developed PVAS: activity simulation test with five participants

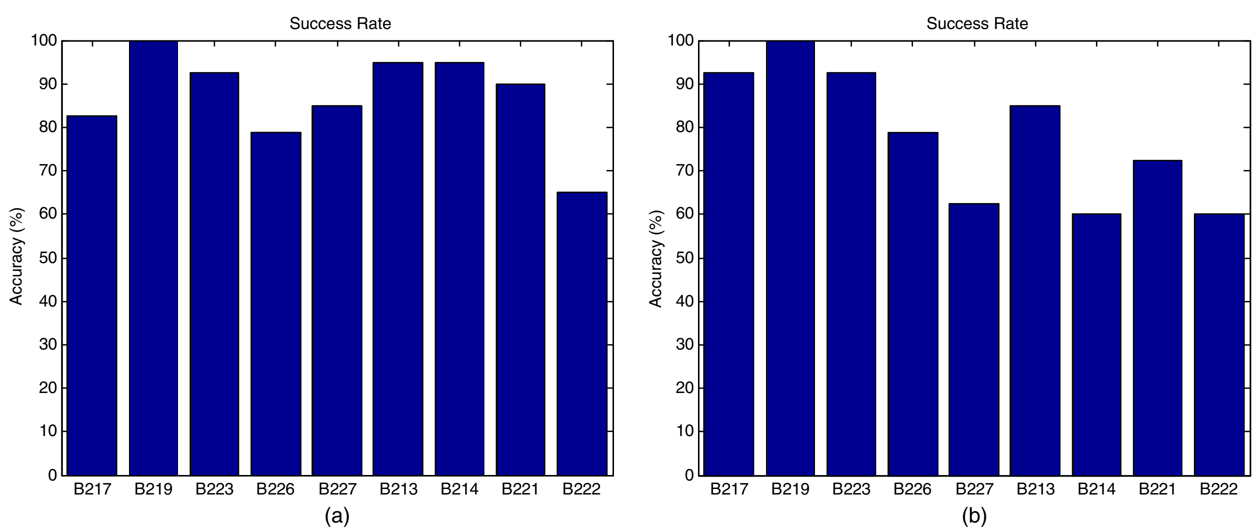


Fig. 17. Success rate for (a) considering directionality; (b) without considering directionality

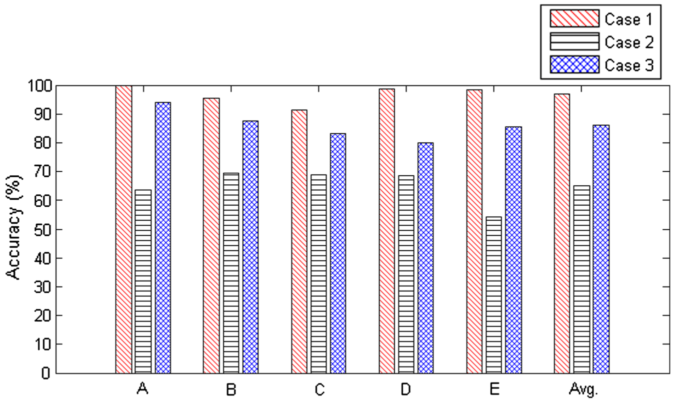


Fig. 18. Accuracy of VAS for each participant

Table 4. Confusion Matrix for Activity Simulation Test

Actual activities	Assessed activities							
	Lay/sit	Stand	Walk	Run	Stair up	Stair down	Roll	Faint
Lay/sit	**1.00**	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Stand	0.05	**0.87**	0.00	0.00	0.00	0.00	0.08	0.00
Walk	0.00	0.00	**0.88**	0.12	0.00	0.00	0.00	0.00
Run	0.00	0.00	0.00	**1.00**	0.00	0.00	0.00	0.00
Stair up	0.50	0.00	0.14	0.00	**0.36**	0.00	0.00	0.00
Stair down	0.00	0.00	0.00	0.23	0.00	**0.77**	0.00	0.00
Roll	0.00	0.00	0.00	0.00	0.00	0.00	**1.00**	0.00
Faint	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**1.00**

Note: Boldface indicates classes classified correctly.

and real-time monitoring of a person equipped with an activity-recording device.

Activity Simulation Test

The first test is an activity simulation test with five participants (A, B, C, D, and E) who each keeping their smartphone in their pants pocket. The participants were asked to simulate the eight activities in their natural way. For each activity, the acceleration, magnetic field, and orientation (calculated using the gravitation and the magnetic field) was obtained for 60 s with a sampling rate of 10 Hz. Then, the first 300 data points for each person were used for training and the other 300 data points for testing.

The result of the test was obtained in Fig. 18 by having three different cases of the training data to check the effect of the participant's unique activity patterns; Case 1: training data from the same participant, Case 2: from one of the other participant, and Case 3: from all other participants. When the trained data from the same participant was used (Case 1), the accuracy is very high, 96.8% on average, reaching 100% for participant A. However, the accuracy decreases to 67.8% on average when the training data was from the other participant (Case 2). Since the training data for all people cannot be obtained for training prior to the disaster, the latter case would be more realistic. When the trained data was obtained from other four participants (Case 3), the success rate significantly improves up to 81% on average. This improvement shows that the data from a person having a similar activity pattern increases the accuracy of the VAS, and a reasonable success rate can be achieved by using the data from more people for training.

The results are also obtained for each activity. Table 4 is a confusion matrix of the activity simulation test. The assessed activities fully agree with actual one for lay/sit, run, roll, and faint. However, going up the stairs and going down the stairs are assessed with low accuracy, since the two activities are actually combined with running or walking. From Table 4, the "Stair Up" was mostly misclassified as "Lay/Sit" or "Walk," and "Stair Down" was mostly misclassified as "Run". This misclassification could be happen because most people tend to walk faster and the stepping down induces a high vertical acceleration level, which is the most dominant feature classifying "Running". Meanwhile, people tend to be slow and more stable when stepping up. This tendency makes a small acceleration level, which is the dominant feature classifying "Lay/Sit" and "Walk". Going up the stairs and going down the stairs would be classified more accurately by using pressure sensors (barometer) in the future work, as this type of sensor is now embedded in most of the newest smartphones.

Real-Time Monitoring

While the first validation test was for stationary results, an additional real-time monitoring test was conducted in order to validate the actual activity of the user. In the real-time monitoring test, the PVAS system was running on the phone with other equipment attached to the body, namely an automatic camera and a commercial health monitoring device called *SenseWear* was attached in armband and could estimate the energy expenditure of the user. As in Fig. 19, a camera was hung around a user's neck and set to take a picture automatically every second in order to record every activity of the user during the test. *SenseWear* was attached to user's arm to compare the estimated activity by PVAS with the energy expenditure estimation. The energy expenditures were expected to be high when engaging in an active activity (e.g., walking) and to be low when performing a static activity (e.g., standing).

The validation test was conducted for about 90 min during the day. As shown in Fig. 20, the PVAS estimated the first half hour as

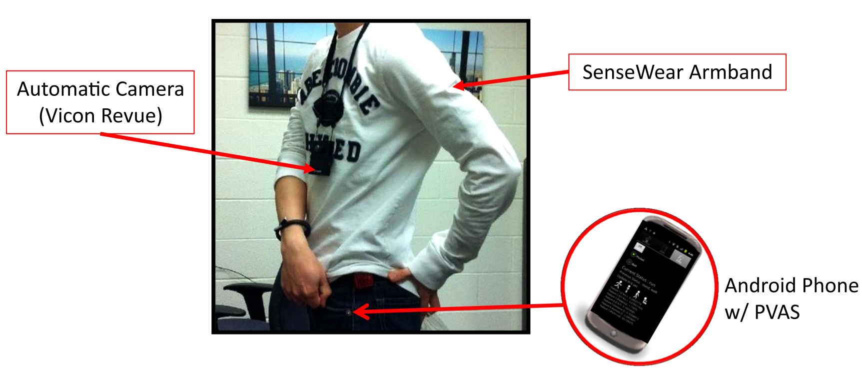


Fig. 19. Configuration of equipment for real-time monitoring test (image by Robin E. Kim)

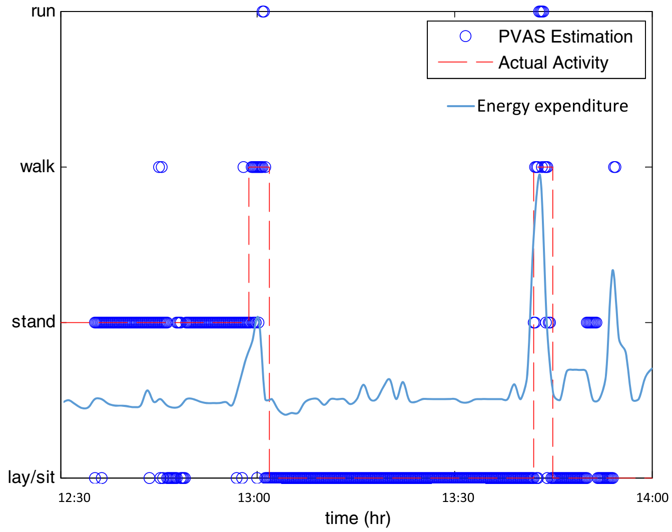


Fig. 20. Comparison of assessed activities with actual activities and energy expenditure during the monitoring test

standing where the picture from the automatic camera indicated the person was actually standing. Also the PVAS estimated the next few minutes as walking and the person was in fact actually walking for those periods. The energy expenditure from the sensors attached on the body showed higher values when the PVAS estimated the activity as walking compared to when it was standing. This result also supports that the PVAS system is estimating the activity correctly.

Conclusion

This paper presented a new system to aid emergency responders plan for evacuation and assistance of victims trapped inside a building based on the sensing and communication capabilities of victims' smartphones. The system estimates the location and physical status of victims inside a building by combining two developed subsystems.

The Victim Positioning System (VPS) estimates the location of the user inside the building by using the received Wi-Fi RSSI by the phone. Wi-Fi RSSI was collected and analyzed in order to discover the characteristic of the signal. A distance-signal relationship test, a directionality test, and a stability test were conducted in order to improve the accuracy of the classification. The modified Naïve Bayes classifier was suggested so that the only selected features could be used for the classification. The fingerprinting was conducted at Parkland College, Illinois, in order to see the performance of the system. The system was able to successfully locate victims at room-level precision with an accuracy of 87% inside a typical building.

The Victim Assessment System (VAS) was able to estimate the activity of the user by using the acceleration and the magnetic field sensor of the phone. The sensor data were collected and analyzed to see the characteristics of data for different activities. These were then used to select the features for the probabilistic classification called Naïve Bayes classifier. The individual activity test showed average accuracy of 81% using training data from five different people. Also the real-time monitoring test, which compared the actual activity recorded by the camera and other sensors, showed that the estimated status of the victim was mostly correct.

The system can potentially be further extended by considering several possible improvements. First, the VPS can be further extended by using other smartphone-embedded sensors such as geo-magnetic fields. The indoor localization system using a geo-magnetic field by itself has some limitation. However by using a geo-magnetic field together with Wi-Fi, it is possible to increase the precision to the meter-level. Second, the VAS will be further extended by using additional sensors (gyroscope and pressure sensor), which are now mostly embedded in the newest smartphones, and also by using multiple additional upcoming wearable devices such as Google Glass. By having additional sensors, not only the accuracy of the current system will increase, but also it will be able to estimate additional activities and adjust for errors resulting from incorrect measurements. Finally, a full-scale test will soon be conducted in order to see the comprehensive performance of the system in a real-world practical disaster recovery scenario. The test will be conducted at Parkland College and Illinois Fire Service Institute with the emergency response time measured both with and without the help of *iRescue* system.

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