Device Free Detection to Improve Construction Work Health and Safety

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ABSTRACT

The Australian construction industry is identified as one among five industries to receive priority attention under the Australian Work Health and Safety Strategy 2012-2022. Among the recorded construction fatalities in 2012, vehicle incidents accounted for 15% and being hit by moving objects accounted for 10%. Tracking of individuals on-site could provide a technological solution to improve safety. This paper proposes a novel non-tagging based wireless networking solution called device free localization to enhance safety on site. Device free localization techniques use radio signal propagation effects such as multi-path fading and shadowing caused by the obstruction(s). The proposed solution defines zones in the construction site. Zone identification is based on the risk associated with the location map of the site. Defining risk profiles considers the activities associated with the geographic location such as loading/unloading areas, truck, and vehicle entering area. The presence of workers entering a particular zone is detected based on this device free detection technique, which will later be extended to localization. This paper proposes a framework for defining risk associated zones for the construction sites for the effective implementation of device-free detection systems. Feasibility of the proposed device free detection technique is verified by preliminary experiments done in an indoor environment with high multi-path fading.

INTRODUCTION

The Australian construction industry employs 1.02 million people and contributes substantially to the Australian economy. However, the construction industry performs poorly in Work Health and Safety (WHS), accounting for 9% of the Australian workforce but 11% of serious workers' compensation claims. From 2008–09 to 2010–11, 123 Australian construction workers died from work-related injuries. This equates to 4.26, nearly twice the national rate of 2.23 deaths per 100,000 workers. Unsurprisingly, given this poor record, The Australian Work Health and Safety Strategy 2012-2022 establishes construction as a priority industry for improvement (Safe Work Australia 2012). Among the recorded fatalities, vehicle incidents accounted for 15% and being hit by moving objects accounted for 10% (Safe Work Australia 2012). A major reason for these incidents is the absence of a systematic mechanism to monitor risk exposure of workers on site.

This paper proposes a novel approach of providing a framework of risk zones on site together with a non-tagging based wireless monitoring mechanism. Most of the wireless positioning techniques are hindered by the problem of multipath propagation which is present in both indoor and outdoor environments. In a multipath environment, the received signal is subject to frequent fluctuations due to movements of vehicles, people and vegetation. The following section discusses the mechanism used to detect construction workers on site. The proposed mechanism uses Line of Sight (LOS) obstruction detection of radio signals by mitigating multipath components of the signal. A parameter which is a representative of the LOS component of the Received Signal Strength (RSS) can be extracted by removing the RSS fluctuations due to multipath propagation. Variations in the LOS parameter so derived, are used to detect the presence of humans on site. The 'Proposed Framework' section discusses on-site zone identification based on the activities associated with each zone. The subsequent section presents the experiment conducted in an indoor environment where significant multipath fading is present. The feasibility of using the proposed technique to detect unauthorized access to risk zones is demonstrated through this experiment.

DEVICE FREE LOCALIZATION

Device Free Localization (DFL) (Patwari 2010) is an emerging research area. In device free localization, moving objects can be detected and/or located without having a device/ tag attached to it or sensing devices in the environment. Some DFL applications are based on sensor networks which probe the radio signals in the environment and are referred to as "RF sensor networks" (Patwari 2010). Arguably, this type of sensing is also referred to as "sensorless sensing"(Woyach et al. 2006) in the literature due to the fact that radio is not generally considered to be a typical sensor. Nevertheless, the DFL paradigm plays a crucial role in wireless networking, which is particularly advantageous in non-invasive tracking applications where tagging a target object is impractical/non-applicable. These applications are also referred to as transceiver-free (Zhang et al. 2007, Zhang and Ni 2009) tracking. Sensing Radio Frequency (RF) energy is also superior to light, infrared, thermal energy or millimeter waves due to its ability to penetrate non-metal walls and smoke (Patwari 2010) when attempting to infer intruder movements.

Various radio channel measurements that can be used in DFL applications including Ultra-Wide Band (UWB), narrow band and Received Signal Strength Indicator (RSSI) (Patwari 2010). Even though RSSI is only a magnitude measurement; it is a readily available and cost-efficient approach over the other technological options.

The magnitude of the RSS will fluctuate due to the objects obstructing the path of a propagating RF signal as well as reflecting objects in the vicinity. Rappaport (2002) discusses these effects in detail. The reflection effect is caused when the signal partially bounces off an object. The refraction effect is caused when the signal direction changes moving from one medium to another. When the signal passes through an object, absorption of the signal takes place. Diffraction is the effect which is caused when the waves spread around an object/obstacle. Scattering occurs when the wave bounces off in multiple directions and polarization is caused when the orientation of the oscillation of the waves can change upon interaction (Rappaport 2002). In addition, if the LOS of the signal is blocked by an object, it causes a sharp decrease in signal strength: shadowing (Wilson and Patwari 2010).

Another effect of signal propagation, which can be a useful source of information for detecting and locating obstructions, is multi-path fading. The original signal can arrive via multiple directions due to the effects such as scattering, diffraction and refraction with surrounding objects. The power of the received signal strength is the sum of destructive or construction multi-path components. Multi-path fading was quantified and experimented in DFL as a variance of RSSI (Wilson 2011) and an absolute value of differences (Zhang et al. 2007).

More recently, RF measurements were used in a number of device free applications including locating people in buildings (Wilson and Patwari 2010), tracking motion behind walls and image the movement (Wilson 2011), tracking a moving target (Zhang et al. 2011), real-time tracking system with a relatively high accuracy (Zhang et al. 2011).

Once the RF radio channel measurements are available, a number of algorithms were used in device free localization in the literature including fingerprint based methods (Viani et al. 2008), adaptive machine learning (Zhang and Ni 2009), radio tomographic imaging and statistical modeling (Wilson and Patwari 2010). In recent studies (Chandrasekara et al. 2011, Edirisinghe et al. 2013), a quantitative measure of LOS obstruction was derived for a single RF link comparing the probability density function of RSSI under normal conditions and a real-time histogram.

RF Finger Printing based LOS Detection. For the focus of this study we use an RF fingerprint based method. An RF fingerprint is a set of parameters which is representative of the RF environment at a specific location. Most of the RF fingerprinting techniques are hindered by the problem of multi-path propagation. As discussed above, even though the transmitter and the receiver are kept fixed, in a multi-path environment, the received signal is subjected to frequent fluctuations due to reflections from various sources such as vehicles, people and vegetation. These effects are referred to as intrinsic motion, while the motion due to an obstruction under localization is referred to as extrinsic motion (Zhao 2011). Noise reduction for variance-based device free localization is proposed (Zhao 2011) where the noise is caused by the intrinsic motion and the variance of intrinsic motion is called the intrinsic signal.

The most commonly used technique for removing RSSI fluctuations due to multi-path is simple time averaging. Fang et al.(2008) investigated a novel approach for extracting a robust signal feature from RSSI measurements in indoor wireless LAN environments. The dynamic multi-path behavior, which can be modeled by a convolution operation in the time domain, is transformed into an additive random variable in the logarithmic spectrum domain. Thus, the convolution process becomes a linear and separable operation which can then be effectively removed (Fang et al. 2008). Such RSSI is referred to as LSA_RSS and it composes of the robust feature extracted from RSSI measurements by eliminating the variations due to multi-path. The following section discusses the LSA_RSS technique.

Log Spectrum Averaging (LSA). Let us consider a sensor network of *M* devices comprises the core of the system. Each sensor keeps a fingerprint of the environment, which is a vector consisting of RSS values from each of the other hearable sensors. The RSS vector of the i^{th} sensor node may be expressed as:

$$S_i = \left[r_{i,1} r_{i,2} \ldots r_{i,(i-1)}, r_{i,(i+1)}, \ldots r_{i,M}\right] \quad (1)$$

Let $y^m(n)$ represent the measured RSS at time instant n from the m^{th} node, $x^m(n)$ represents the decayed LOS signal in free space, $v^m(n)$ represents the communication noise. The time varying multipath is captured by $h^m(n)$ representing the channel attenuation for each delayed signal.

Let L be the number of delayed paths so that the measured signal from the m^{th} node is given by,

$$y^m(n) = \sum_{l=0}^{L} h^m(l)\left[x^m(n-l) + v^m(n-l)\right]$$

$$1 < m < M,\ 0 < l < L\text{-}1,\ 0 < n < N\text{-}1 \quad (2)$$

M is the number of nodes and N is the number of RSS measurement samples observed.

$$y^m(n) = x^m(n) \otimes h^m(n) + v^m(n) \otimes h^m(n) \quad (3)$$

where $\otimes$ denotes the convolution operation.

Mitigating RSS fluctuations due to multipath effects is done by transforming the RSS in to the log frequency domain using the following steps:

$$R_y^m(k) = \frac{1}{(N-k)} \sum_{n=0}^{N-1} y^m(n).\, y^m(n+k) \quad (4)$$

Where $0 < k < K$-1 and k is the index of autocorrelation function and K is the length of the processing window.

Using above definition we can show that

$$R_y^m(k) = R_x^m(k) \otimes h^m(k) \otimes h^m(-k) + R_v^m(k) \otimes h^m(k) \otimes h^m(-k) \quad (5)$$

$R_y^m(k), R_x^m(k)$ and $R_v^m(k)$ represent autocorrelation sequences for measured RSS, LOS signal and communication noise. Taking the discrete Fourier Transform,

$$S_y^m(f) = \left[S_x^m(f) + S_v^m(f)\right].\, |H^m(f)|^2 \quad (6)$$

$S_y^m(f), S_x^m(f)$ and $S_v^m(f)$ represent power spectra for measured RSS, LOS signal and communication noise respectively. The frequency index is f with F being the length of the power spectrum. Here $0 < f < F$-1 and $1 < m < M$, M is the total number of nodes in the mesh. Taking the logarithm of both sides of (6) we get the *log-spectrum* of $y^m(n)$ as,

$$\log S_y^m(f) = \log\left[S_x^m(f) + S_v^m(f)\right] + 2\log|H^m(f)| \quad (7)$$

The multipath component has been converted to an additive random variable, whose effect can be removed by averaging. Thus, the quantity LSA_RSS^m for a given point is defined as,

$$LSA\_RSS^{m} = \frac{1}{F} . \sum_{f=0}^{F-1} \log S_{y}^{m}(f) \tag{8}$$

This is the robust feature extracted from RSS measurements by eliminating the variations due to multipath. Comparatively, the time-averaged RSS measurement from the m^{th} node is expressed as:

$$TA\_RSS^{m} = \frac{1}{N} . \sum_{n=0}^{N-1} y^{m}(n) \tag{9}$$

Previous work reported in detecting elephants (Edirisinghe et al. 2013) and people (Chandrasekara et al. 2011) applied the LSA_RSS technique to mitigate fluctuations in outdoor environments, and showed that it was successful. We investigate the application of this technique as well as time averaging of RSSI to an indoor environment in the study reported in this paper. We investigate the improvement in robustness achieved by (8) compared to (9) in the 'Feasibility Study' section below.

PROPOSED FRAMEWORK

California Construction Academy identifies a list of top 16 construction hazards (2013). Hazard Risk Control Reference Source and Guide (Griffith University 2013) provides a model of hazard-cause-control measures for construction industry. Notably, this model proposes to have traditional control measures such as "use of safety signs" and "Sign and fence to prevent access" for some hazards. The device free detection we propose is a novel technological solution over the traditional control measures.

The framework we propose for identifying risk zones within the construction site is based on the construction hazards and activities (can be con-current and overlapping) within the zone. Based on the hazards the risk profiles are associated to the geographical areas/zones in the site. The presence of unauthorized/ risk exposure access to the zone by workers is detected based on device free detection technique proposed above. Figure 1 illustrated the proposed framework.

Activities within the zone include and are not limited to working below elevated work surfaces, suspended loads, material storage, work under lifting loads, moving materials, heavy construction equipment in operation, vehicle traffic, zone characteristics leading to unsafe working conditions including open holes, trenches, or stakes, excavation and trenching, using temporary platforms such as scaffolds, etc. Potential hazards include falls, electrocution/electrical, caught-in and struck-by as a consequences such as unsafe scaffolds, overloaded vehicle and forklifts, unsafe electrical equipment & connections, unsafe cantilever loading platforms, falling objects, overloaded/unstable/unsafe mobile equipment and unsafe access/egress, etc.

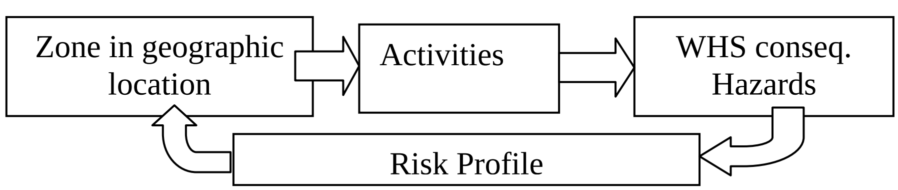

Figure 1. Framework to define Risk-Profile on Zones.

In the proposed framework the risk zones are categorized based on hazards/activities and consequences. i.e. colors of safety be used for zones. The proposed risk profiles of zones are as follows.

- Danger - Deadly hazards/ high risk consequences of the unsafe/unstable activity (Including deadly hazards such as falls, electrocution/electrical, caught-in and struck-by)
  e.g. exclusion zone when the mobile plant in operation (Teizer et al. 2010)
- Warning – Moderate risk hazards that might cause possible accidents. The consequences of the activities are moderate.(Including moderate risk hazards such as lifting and body straining)
  e.g. materials handed by workers in a storage zone (Cheng et al. 2013)
- Caution – Low risk hazards such as noise.
  e.g. zone in which noisy equipment in operation
- Safety – No risk associated
  e.g. administration office or travel (Cheng et al. 2013) path for workers

This framework enables visualizing construction WHS hazard dynamics in a geographic map.

FEAIBILITY STUDY

The ability to use the LOS obstruction based device free detection technique to detect humans in an indoor environment is experimented in a detached residence located on a main street where multipath effect is significantly high due to moving vehicles. Figure 2 shows the results for a set of measurements taken. The LSA_RSS was calculated using Equation (8) by segmenting the measurement data into non-overlapping windows (Segmented LSA_RSS) as well as using a moving window (Moving LSA_RSS). The time averaging computation in Equation (9) was done for a simple moving window (Moving TA_RSS) for the comparison.

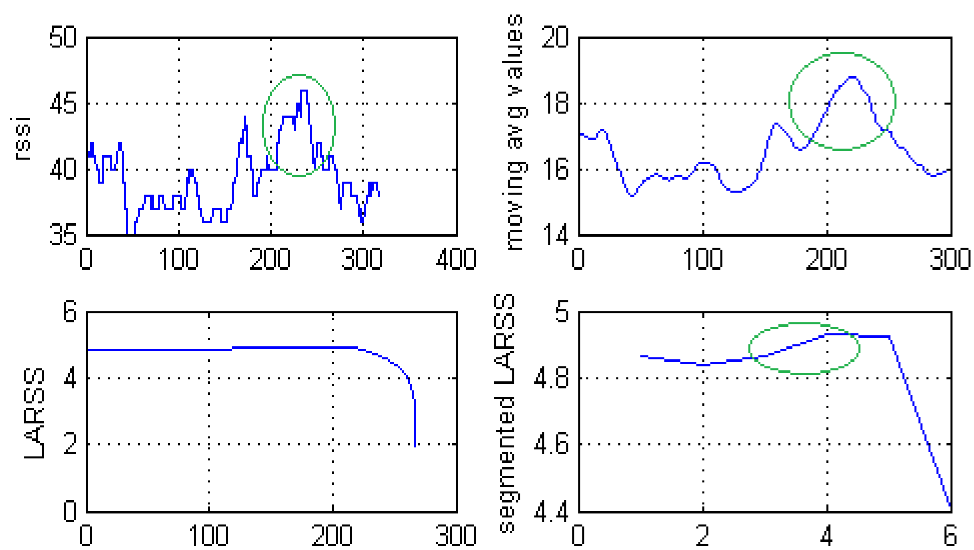

Figure 2. RSSI measurements, TA_RSS and LSA_RSS.

In Figure 2 sharp fluctuations (green circle) in RSSI were noted to be LOS obstructions caused by the movement of a human. The smaller-scale fluctuations are due to multi-path propagation.

Qualitative evaluation of the Model for RSSI variation in a multi-path channel shows that the fluctuations are reduced considerably in the LSA_RSS technique compared to TA_RSS. It is also seen that in LSA_RSS, fluctuations due to obstructions are retained while those due to multi-path propagation are smoothed.
The preliminary experiment results verify the ability of the LSA_RSS technique to detect humans in an indoor environment where high multipath fading is presence.

CONCLUSION

This paper proposes a framework that enables defining risk-profile for zones in a construction site and a mechanism to detect the presence of construction workers on high risk zones. The device free detection technique mitigates multi-path effect in highly dynamic construction sites in order to detect/locate workers.

The work reported in this paper is the first phase of an ongoing work for a risk exposure monitoring and detection system for workers on a site. The preliminary experiments verify the feasibility of using the device free detection technique in an indoor environment which has high multipath fading. Further experiments will be conducted to test the ability to detect vehicles, humans and construction work simultaneously in the same experimental set up on a construction site. The ability to set thresholds to detect each object and to differentiate the smaller–scale multipath fluctuations for a more robust system will be investigated. The proposed risk-profile framework is further to be verified at a nominated construction site for the project.

The construction site has a mix of both indoor and outdoor environments depending on the construction phase. The next stage is to conduct the experiments at varying phases of the construction project life-cycle to cover both indoor and outdoor environments at the nominated site. Sensitivity and accuracy of the proposed method in highly dynamic construction site with the presence of multipath fading will be investigated. Future work also includes the investigation of monitoring and alerting application characteristics such as false alarms and misses.

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