RSSI-based Device Free Localization for Elderly Care Application

Shaufikah Shukri[1,2], Latifah Munirah Kamarudin[1,2], David Lorater Ndzi[3], Ammar Zakaria[2,4], Saidatul Norlyna Azemi[1], Kamarulzaman Kamarudin[2,4] and Syed Muhammad Mamduh Syed Zakaria[2]

[1]*School of Computer and Communication Engineering, Universiti Malaysia Perlis, Arau, Perlis, Malaysia*

[2]*Centre of Excellence for Advanced Sensor and Technology, University Malaysia Perlis, Jejawi, Perlis, Malaysia*

[3]*School of Engineering and Computing, University of the West of Scotland, Paisley, Scotland*

[4]*School of Microelectronic Engineering, University Malaysia Perlis, Arau, Perlis, Malaysia*

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Abstract: Device-Free Localization (DFL) is an effective human localizing system that exploits changes in radio signals strength of radio network. DFL is playing a critical role in many applications such as elderly care, intrusion detection, smart home, etc. DFL is ideal for monitoring the elderly activities without causing any physical discomfort with the wearable devices. It is challenging for elderly to remember each day to wear or to activate those devices. The purpose of this study is to select the best DFL methods in term of detection and tracking accuracy, which is suitable for human monitoring application especially for elderly and disable people. This paper proposes an RSSI-based DFL system that can be used to detect and locate elderly people in an area of interest (AoI) using changes in signal strength measurements. An attenuation-based and variance based methods have been introduced in the proposed DFL system. In stationary people scenario, attenuation-based method managed to accurately detect the presence of human, which is very suitable for elderly care application compared to variance-based DFL. The result shows that attenuation-based method managed to detect all trajectories of moving people with 100% detection accuracy while variance-based method only give 71.74% accuracy.

1 INTRODUCTION

Device Free Localization (DFL) is a passive indoor localization system that uses the changes in the Received Signal Strength Indicator (RSSI) measurement to form the location information metric about the location of person or object being tracked. The DFL system monitors the fluctuation in the received signal strength caused by the presence of a human body in an indoor environment. More than 70% of human body contains water that can absorb and attenuate the radio signal wave at the frequency of 2.4 GHz which is also the resonance frequency of water (Deak et al., 2013). Several terms has been used by the researcher to described DFL system. Patrawi et al. (2010) defined DFL research area as radio frequency (RF) tomography, RF sensor network, and sensorless sensing. Due to the increasing number of elderly and disabled people population whom requiring better quality of life and demand more healthcare and assistance services, Internet of Things (IoT) has great potential to support the society and health care providers by introducing the combination of Ambient Intelligence and DFL technology into residential monitoring system known as Ambient Assisted Living (AAL). The Ambient Intelligence vision is to build an intelligent home with the help of smart devices and appliances in order to increase the safety and wellbeing in that particular home (Rose et al., 2015).

The basic idea of IoT is the transformation of everyday devices into smart things which have the ability to sense, interpret and react to the environment through application by utilizing the embedded technology (Domingo, 2012).The main strength of IoT is to create smart environment applications that will give significant impact to the real world scenarios and bring improvement in people's daily lives as well as provide intelligence and comforts to the end user especially the disabled by saving times and resources. Vermesan et al. (2014) stated that at the year of 2011 the number of

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available IoT devices has already exceeded the number of human being on planet Earth, and he estimated by the year of 2020 the IoT devices are expected to number in range of 26 billion to 50 billion. Examples of IoT application area include Building, Healthcare, Lifestyle, Transportation, City, Factory, Agriculture, Supply chain, Environment and Energy and Tourism (Vermesan et al., 2014).

We strongly believe that the Internet of Things can offer elderly people the assistance and support they need to achieve a better quality of life. Therefore, in this paper we proposed RSSI based indoor localization system that is able to estimate the location of people by monitoring the changes in RF signal field occurring in the monitored network area. This paper introduces a similar concept of device free human presence detection system using attenuation-based and variance based methods that varies in terms of experimental designs. The aim of this paper is to evaluate and compare the performance of attenuation-based and variance-based method in DFL system in detecting moving and static entities inside a building for elderly care application. The remainder of this paper is organized as follows: Section 2 described the existing works related to elderly care applications, Section 3 presents the proposed model-based methods used to design algorithms using signal strength measurements, Section 4 describe the experimental setup, hardware, and development of algorithm, and Section 5 reports in details the result and analysis of the experiment. Finally, Section 6 concludes and discusses the recent improvement strategies of DFL system for elderly care application.

2 RELATED WORKS

Elderly care applications has been introduced to improve the quality of life of seniors citizen whose health is deteriorating due to increasing of age, and at the same time reducing healthcare resources as well as costs. The detection and tracking accuracy of moving people in indoor and domestic environment is one of the most important requirement in elderly care application. The information gathered from sensor nodes implemented for indoor localization are multiple purposes and useful for elderly care application to monitor daily activities, observe tendencies of people, and alert the caretaker or doctors in the case of abnormal behaviour of events (Chironi et al., 2015).

In recent years, DFL for indoor environment topic has become increasing popular among research community and different detection system and sensing technology have been developed in the context of elderly care application. DFL technology provides considerable advantages over other technologies since there is no requirement for the tracked entities to carry or wear any radio device or sensor. This advantage makes DFL system very suitable for monitoring the elder people activities without causing them physical discomfort with the wearable devices or sensors. It is challenging for elder people to remember each day to wear or to activate those devices.

Kaltiokallio et al. (2012) presented an RSS-based DFL system for long-term residential monitoring purpose that is able to provide accurate location estimation. An online recalibration method was proposed which enable proposed system to adapt to the small changes in the real radio network environment cause by daily routines for the long-term deployment. They introduced a Finite-state Machine (FSM) model which defines the location specification of the person at different AoI inside the house and linked the system to a Twitter account to update the affected AoI. The proposed system was able to accurately locate the monitored person while carried out his daily routine.

Jin et al. (2015) proposed a passive elderly care localization system using Nearest Neighbour-based (NN) method to estimate the person location in the monitored area and compared with Support Vector Machine (SVM) method. They divided their experiment into offline and online phase where indoor position information was utilized to construct the daily motion pattern of an elderly person. They show that NN method performs better than SVM in more complex environment and it is able to estimate on average the location of tracked person with a very high accuracy, 93.0655%.

Bocca et al. (2012) explore the use of Radio Tomographic Imaging (RTI) in the context of assisted living application. RTI is a technique that produces real-time images of the changes in received signal strength caused by human presence in the monitored radio network environment which can be used to estimate the location of people. They found out that the change in RSSI depends on measured frequency channel and proposed “fade level” concept to their attenuation based RTI system. The regularized least-square approach was selected as regularization method to solve the ill-posed inverse problem when estimating the real-time image. They demonstrated that the average localization error of the system is 0.23m. The proposed system can accurately localize a target without participating in the localization process, hence makes the RF technology a very attractive solution for elderly-care application.

3 DFL CONCEPT

DFL is an effective human presence detecting technology that does not require the tracked entities to carry any additional radio devices or to be cooperatively participating with the localization process. It performs on the principle that the human body will absorb/reflect the signal strength of indoor wireless links being transmitted, when moving across the Line-of-Sight (LoS) link of a transmitter and receiver. By exploiting the changes on the received signal strength of a given radio link, the DFL system is able to detect the area where the tracked entity is moving into. For example, if a person enters a room as shown in Figure 1, the algorithm of detection system will automatically detect that there is a changes on the signal strength on the LoS link between node N1 and N2 hence the localization system will conclude that the user is entering the area A1.

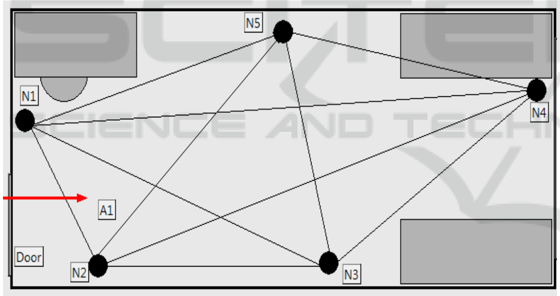

Figure 1: The proposed RSSI-based DFL system.

The advantage of model-based methods reported by Kanso et al. (2009), Chen et al. (2011), Kaltiokallio et al. (2011), Wilson et al. (2010, 2011), and Zhao et al. (2011), is that training data of each possible location in AoI is not required. These methods use an elliptical model to relate people's location to different forms of RSSI measurements. Wilson et al. (2010) use the model to relate the location of a person with the absolute RSSI changes from an "empty-room" calibration, where there is no human presence in the network area. The model is based on the fact that if a person stands inside an elliptical area covered by a link between two nodes within N voxel of network region, the person has certain effect on the RSSI link measurement; otherwise, there is no effect from the person.

3.1 Attenuation-based Method

For attenuation-based model, let consider an empty room scenario of radio network for certain period of time. During this period, the RSSI of L radio links are measured. The average RSSI of unaffected link is represented using the sample mean, denoted as $\hat{r}_l$. In real environment, the RSSI measured by the receiver of link l at time t can be described as

$$r_l(t) = P_l - L_l - S_l(t) - F_l(t) - v_l(t) \qquad (1)$$

where P_l is the transmitted power, $S_l(t)$ is the shadowing loss, $F_l(t)$ is fading loss from multipath signals, L_l is static losses, and $v_l(t)$ is the measurement noise. Let consider that changes in attenuation has great impact to the received signal, hence static losses L_l which caused by distance, antenna patterns, device performance, etc. can be removed over time to simplify the problem. The shadowing loss $S_l(t)$ due to objects that attenuate the signal for a link can be described as

$$S_l(t) = r_l(t) - P_l + F_l(t) + v_l(t). \qquad (2)$$

The fading loss and measurement noise can be grouped as noise n_l and described as

$$n_l = F_l(t) + v_l(t) \qquad (3)$$

hence $S_l(t)$ can be written as

$$S_l(t) = r_l(t) - P_l + n_l(t). \qquad (4)$$

Due to the presence of noise $n_l(t)$, the shadowing loss cannot be measured directly. Thus, the shadowing loss is estimated using the average RSSI $\hat{r}_l$, measured during empty room scenario

$$S_l(t) = r_l(t) - \hat{r}_l. \qquad (5)$$

The RSSI attenuation or difference between the current RSSI measurement and the average RSS measured during empty room scenario when no person is in the monitored area at time t is calculated as

$$\Delta r_l(t) = r_l(t) - \hat{r}_l. \qquad (6)$$

3.2 Variance-based Method

The attenuation-based method requires an initial calibration of the system in an empty room scenario with no objects present in the monitoring area. Recalibration is required when there is changes in the environment, e.g., when any objects are placed to other position, otherwise the system will lose its accuracy. Variance-based method can be applied since the changes in RSSI due to human presence on the link can be quantifies as the unbiased sample variance of windowed RSS variance (McCracken et al., 2013). Zhao et al. (2011) described the windowed RSSI variance as

$$Var_l(t) = \frac{1}{p-1}\sum_{i=0}^{p-1}(\bar{s}_l(t) - s_l(t-i))^2 \quad (7)$$

where p is the window length, and $\bar{s}_l(t)$ is the average sample in this window period and can be written as

$$\bar{s}_l(t) = \frac{1}{p}\sum_{i=0}^{p-1} s_l(t-i) \quad (8)$$

Variance-based RTI does not require empty room scenario training data of the system and can easily adapt to the changes in the environment.

4 EXPERIMENTS

In the previous work (Shukri et al., 2016), we proposed a RSSI-based DFL system using a pair of IRIS mote to study the impact of human body to the signal strength in static and moving condition on single network link. The proposed system proved that the signal strength tends to fluctuate by average of 3.97 dBm with the presence of static human body on the LOS link and human detection and tracking of stationary target is possible to within 1.0 m distance from LOS link. Meanwhile, human movement across the LOS link can cause significant signal variation ranging from 10 to 15 dBm. In this paper, we proposed an RSSI-based DFL system with the configuration of multiple nodes (multiple network links).

The experiments were conducted in Research Room located at the first floor of Centre of Excellence for Advanced Sensor and Technology (CEASTech), University of Malaysia Perlis (UniMAP), and the test-bed setups are illustrated in Figure 2. The area of the Research Room is 2.5 m by 5.0 m and the ceiling height is 2.5 m. Three of the walls are made of concrete, and one is containing glass window. A wireless radio network consists of six XM2110 IRIS motes (Memsic Inc.) made by MEMSIC configured as the transmitters (N1, N2, N3, N4 and N5) and a receiver (Rx). Each node comprises of 1.2 inch 3 dBi omni-directional antenna gain in azimuth with transmission rate of 250 kbps.

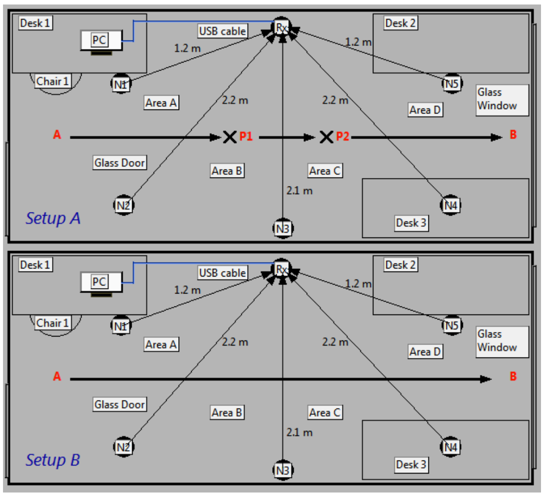

Figure 2: Test-bed setups for Exp.2 (Setup A) and Exp.3 (Setup B).

The nodes were placed at different position in the room with different distance from the receiver. Each node, placed with height of 1m above the floor, operated in the 2.4 GHz frequency band and used IEEE 802.15.4 (Zigbee) standard for the transmission protocol. The receiver was mounted on a MIB520 interface board and connected to a laptop via USB port. The XM2110 IRIS for the transmitters was programmed to transmit an empty packet every 1s. The receiver was programmed with Xsniffer firmware to sniff and collect the received signal strength from the transmitting nodes.

The collected information was transferred to a laptop to be processed by a DFL detection algorithm developed using LabVIEW programming language. The RF power level was set to 3.2 dBm transmitting at the strongest power level. RF channel 26 (2.48 GHz frequency band) was used to avoid co-channel interference to the radio signal during experiment since this channel 26 is proven as the most stable with least interference among other available channel based on the wireless network coexistence study performed by Guo et al. (2012). Each node was programmed with the same Group IDs, RF channels and RF power for successful radio communication.

During RF packets transmissions, the receiver will automatically detect the RF strength level of each node and send the information to a laptop for processing. The nodes are placed at the height of 1.0 m above the floor to eliminate the Fresnel Zone effect. Turner et al. (2013) studied the allowable height for obstruction within the clear Fresnel Zone is when both transmitter and receiver are mounted 1 .0 m above the floor. They also stated that to ensure the optimum radio performance, the motes must be kept clear from the wall, ceiling and floor for about 0.2 m.

4.1 RSSI Analysis

To study and analyse the RSSI attenuation and variance patterns of human presence in the indoor environment of multiple nodes, we have decided to record the RSSI information under the following scenarios:

- No obstruction was present (Exp.1): 3600 samples (for duration of 1 hour) of RSSI measurements were taken to analyse the RSSI trend during day time. This experiment was carried out to monitor the baseline reading of all network environments.
- A body stands at pre-defined positions (Exp.2): A person was instructed to walk from point A to point B and stand at a pre-defined position without moving for pre-determined amount of time before walking to the next position as shown in Setup A of Figure 2. The pre-defined positions labeled as 'X' were denoted as P1 and P2. Position of P1 is located in Area B between link N2 and N3. Position of P2 is located in Area C between link N3 and N4. The objective of this third experiment is to compare the detection result and localization accuracy between attenuation-based DFL and variance-based DFL for human presence in static condition.
- A body crossed the network link (Exp.3): A person was instructed to walk from point A to B as shown in Setup B of Figure 2, and walked back to point A at a moderate pace across the network links. This experiment was carried out to monitor significant signal attenuation when a person crossed the LoS links. Experiment was repeated and the number of crossing was increased from two to ten times. This experiment was carried out to monitor the RSSI pattern when a person crossed the LoS links and measured nodes sensitivity in detecting movement.

All RSSI information collected from the experiment were transferred to a laptop to be process using a DFL detection system developed using LabView programming language. For attenuation-based DFL system, it is important to obtain the baseline or average RSSI during the monitored area is empty. The baseline indicates the reference level which will be used to estimate the attenuation in RSSI signal when person entered the monitored area or crossed the radio links. The attenuation, α is estimated as the difference between RSSI measured at time *t*, *ri(t)* and the baseline of RSSI, $\hat{r}$:

$$\alpha = r_i(t) - \hat{r} \tag{9}$$

where $\hat{r}$ computed using mode function which selects the value that occur the most often

$$\hat{r} = Mode\,\{r_i\} \tag{10}$$

If the person moving across the radio network area, the signal will experience large attenuation in RSSI as the obstruction by human body contributes to signal degradation for a certain time frame. The baseline will give very small attenuation values (small fluctuations), thus indicating the absence of people. If the person is moving across the network several times, the graph of RSSI value will show declines in reading according to the number of crossing.

4.2 Detection Algorithm

The attenuation-based method requires an initial The proposed detection algorithm used in the LabView program is based on the observation of RSSI attenuation. RSSI attenuation is one of the valuable parameters to detect activities or any changes occurred in wireless radio network. The RSSI attenuation reading shows that there are changes in the RSSI behaviour where the radio links of the network were obstructed or blocked. In this study, the value of RSSI attenuation increases (in negative reading) when a person walked across the network links of wireless nodes. When the person walked away from the monitored area, the RSSI attenuation reads zero readings shows that there are no changes in the monitored area. The threshold value for attenuation, denoted as $\bar{\alpha}$ is determined by taking the average attenuation when people crossing the network links.

Based on the above consideration, a detection algorithm has been deployed and the process flow is shown in Figure 3. When the receiver received RSSI from each node, it sends the information to laptop for data processing and analysis. Baseline reading of each node is computed using mode function and RSSI graphs of each node are updated for viewing purposes. RSSI measurements from each window are stored and updated. The attenuation of each link is evaluated. When $\Delta\alpha > \bar{\alpha}$, the link between node i and receiver is assumed to be unaffected and go back to the initial step for the measurement of next window. When $\Delta\alpha \leq \bar{\alpha}$, human crossing is detected, the LED that show human presence is blinked, the counter for occurrence is increased, and go back to the initial step to measure RSSI of next window.

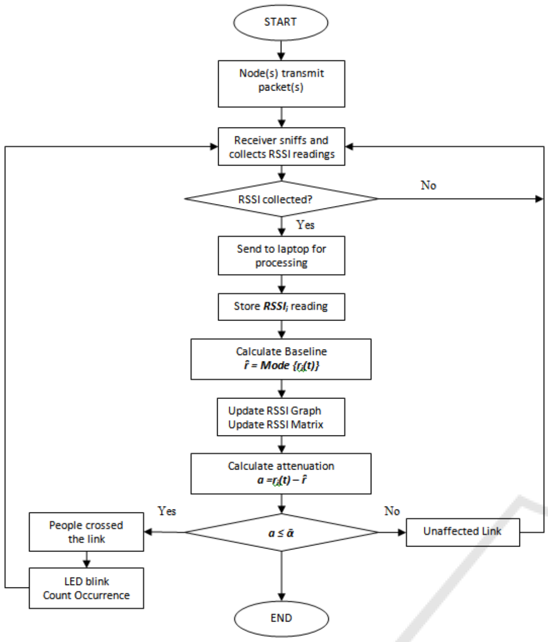

Figure 3: Process flow of proposed detection system.

5 EXPERIMENTAL RESULTS AND ANALYSIS

The following results are presented in three sections; empty room scenario, human presence with movement scenario and human presence with static scenario. The empty room scenario only focuses on the RSSI measurement during daytime since previous work (Shukri et al., 2016) has covered RSSI measurement during both day time and at night. For human presence with movement scenario, a person walks across the network link two times and ten times at a moderate pace. In human presence with static scenario, a person stands at different positions for certain period of time. The differences in the signal attenuations can be observed when there is human presence in the different environments. All the RSSI measurements from each experiment were automatically plotted on graph which is available on the Front Panel of LabVIEW program. The day results allow the analysis of human presence on WSN and show the effect of building materials, other WiFi devices, and node battery strength on the signal strength.

5.1 Empty Room Scenario

In empty room scenario where no obstruction presence in the Research Room, the day time reading were taken during working hours from 9:00 to 17:00. Figure 4 shows the RSSI values of each node measured during day time. The RSSI values measured for 3600 samples range from -51d to -56 dBm for node N1, from -52 to -57 dBm for N2, from -49 to -52 dBm for N3, from -51 to -55 dBm for N4, and from -46 to -47 dBm for N5, respectively. In previous work (Shukri et al., 2016), the RSSI measurements for empty room scenario were collected during daytime and at night; and the signal strength were found to be unstable with several small fluctuations during daytime due the presence of several wireless devices operating for data collection, human movement inside the building, and moving vehicles on the nearby road (Kassem et al., 2012), compared to the signal strength which are more stable at night.

In this work, the experiment for empty room scenario only focuses on the RSSI measurement during daytime to monitor the stability of the nodes in transmitting packets and the reliability of the data collected. The baseline was computed using mode function which selects the value that occurs the most often for every node as shown in Table 1. The RSSI and baseline readings for each links are different since the nodes were placed at different position inside the room. The battery performance has a significant impact to the RSSI readings as well where signal degradation happens when the battery is low since the node does not have enough power to transmit or received the signal.

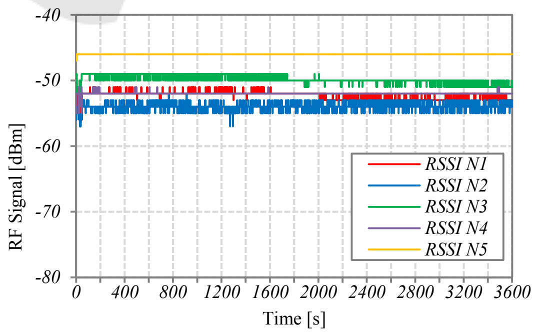

Figure 4: RSSI measured in the monitored area during day time.

Table 1: Baseline reading measured for each node.

Node	Baseline (dBm)
N1	-52
N2	-54
N3	-50
N4	-52
N5	-46

5.2 Stationary People Scenario

Exp.2 focuses on monitoring the changes in received signal strength of multiple network links in the presence of human without movement. In the real world scenario, people living in a house always performed activities that did not required them to move at considerable amounts of time such as sitting or lying on the coach while watching television, sleeping on bed, sitting at dining table and etc. This section discussed on the capabilities of attenuation-based and variance-based DFL system in localizing stationary people.

Figure 5 and Figure 6 show the attenuation and variance values of the network links when a person stand at pre-defined position P1 and P2 as depicted in Setup A of Figure 2 for about 20 sec, respectively. As illustrated in Figure 5, the attenuation of the RSSI values decreases at pre-determined times showing that a person standing at fixed position P1 and P2. When the person moved away from the positions leaving the area empty, the attenuation reading of affected links goes back to the normal (empty area) readings. For eg., when a person is standing at position P1 (Area B) for about 20 sec starting at t=30 sec, there are changes on the attenuation values of N1, N2 and N3 since these three nodes located near to position P1. When the person started to move and stand at position P2 after 20 sec, the attenuation values of nodes N1, N2 and N3 experience normal (empty area) value. The presence of human near to the network links changes considerably the RSSI and attenuation measured on the affected links.

For each sample window, the collected RSSI values been averaged for every four second, and the variance of each sample window have been computed. As per illustrated in Figure 6, the variance values only experiences peaks which indicate that the person moved crossed the network links into and away from the pre-defined position P1 and P2, but did not show that the person was standing at Position P1 and P2 at pre-determined times. For eg., the variance value of N2 is expected to show changes from 7th to 13th sample window interval which indicates that a person is standing at Position P1 (Area A), however it only shows two peaks at 7th and 13th sample window interval which indicate that the person is crossing the network link of node N2. This proved that variance-based DFL is not capable of localizing stationary people since the measurements are based on a windowed variance of RSSI.

The experiments conducted in these section shows that human presence in stationary condition contributes to the changes of signal strength by introducing the shadowing and multipath effect. The results proved that localization and detection of stationary people in multiple network links environment is possible using attenuation-based. However, the variance-based DFL is not suitable for elderly-care application due to its incompetency of localizing stationary people.

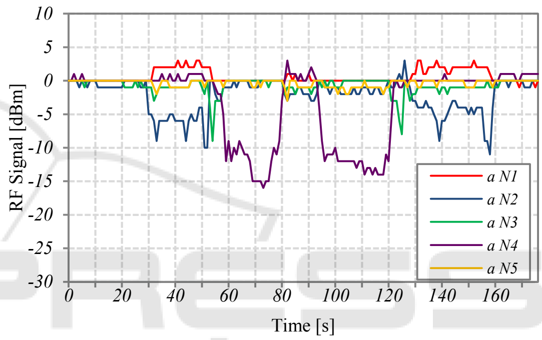

Figure 5: Attenuation values of the network links in Setup B when a person stands at pre-defined position.

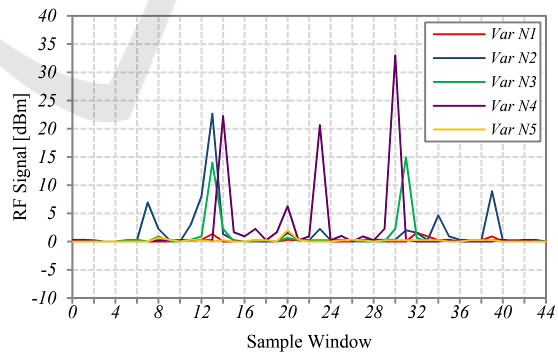

Figure 6: Variance values of the network links in Setup B when a person stands at pre-defined position.

5.3 Moving People Scenario

In this section, the changes on received signal strength due to human movement across the LoS links are discussed. Two experiments have been conducted in this section with different number of crossing. In the first experiment, a body was instructed to cross the monitored area twice while in the second experiment the number of crossing was increased to ten times. The results have been analyzed in both attenuation-based and variance-based DFL.

5.3.1 Two Times Crossing

Figure 7 shows the RSSI attenuation values of each network links in the monitored area when a person crossed the network links twice. It can be observed that the signal strength of affected network links decrease when the person crossed the network links from point A to B and back to point A. The affected network links are N2, N3 and N4.

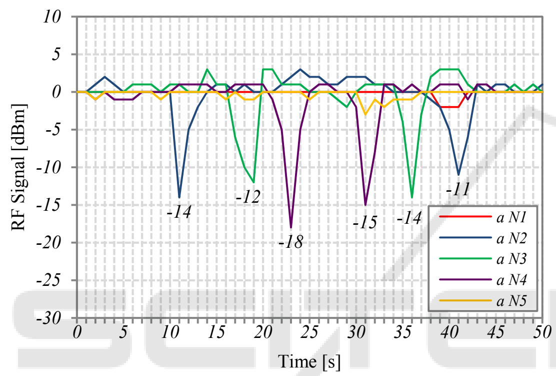

Figure 7: Attenuation value of the links in Setup B when a person crossed the link 2 times.

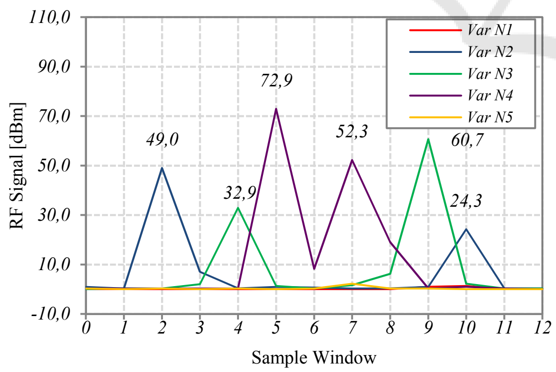

Figure 8: Variance of the links in Setup B when a person crossed the link 2 times.

The graph from Figure 7 shows that the attenuation-based DFL system can accurately detect the sequence of affected links when a person moving across the network, hence the area of interest can be determined. From point A to B, a person will first cross the link of node N2 at time equal to 11 sec which determined that the person moved from Area A to Area B. The person then walked from Area B to Area C by crossing N3 link at time equal to 19 sec, and at time equal to 23 sec the person crossed N4 link indicates that he moved from Area C to Area D. Significant signal attenuations are observed to be range from -11 dBm to -18 dBm when the person crossed the network links.

Figure 8 shows the variance values of the same scenario computed using variance-based DFL. The first crossing was detected to be at 2nd, 4th and 5th sample windows for N2, N3 and N4 links with the variance values of 49, 32.9 and 72.9 respectively. The second crossing was detected to be at 7th, 9th and 10th sample windows for N4, N3 and N2 links with the variance values of 52.3, 60.7 and 24.3 respectively. The attenuation and variance values of affected links from both Figure 7 and Figure 8 experiences two peaks, as expected since during experiment the user crossed the link two times. No signal large fluctuation observed on links N1-Rx and N5-Rx since there is no human presence across these links.

5.3.2 Ten Times Crossing

Exp. 3 was repeated and the number of crossing was increased from two to ten times. Figure 9 shows the RSSI attenuation values of multiple network links when a person crossed the link ten times. It can be observed that the signal strength of affected network links N2, N3 and N4 decrease when the person crossed the network area ten times. Similar to previous experiment with less number of crossings, the attenuation-based DFL system can accurately detect the number of crossing as well as sequence of affected links with 100% accuracy when a person moving across the network several times; hence can the area of interest can be determined. As per expected, ten decreasing peaks experienced by the attenuation values of affected links in Figure 9 since during experiment the user crossed the network links ten times. The variance values computed using variance-based method of the same scenario is depicted in Figure 10. It can be observed that the variance values of affected network links N2, N3 and N4 varies when the person crossed the network area ten times. As per expected, ten peaks experienced by the variance values of affected links ranging from 8.25 to 157.33 as shown in Figure 10 since during experiment the user crossed the network links ten times.

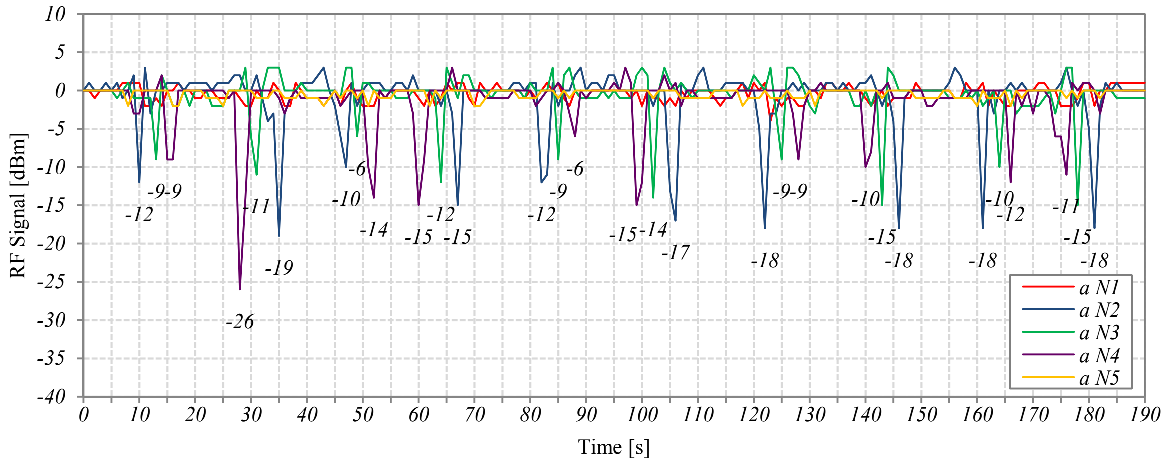

Figure 9: Attenuation values of the link in Setup A when a person crossed the link 10 times.

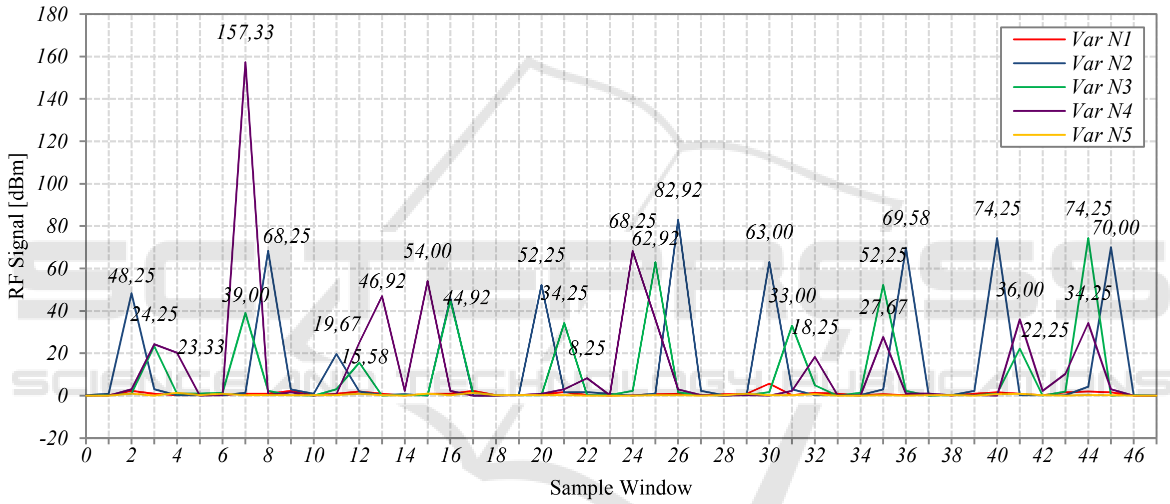

Figure 10: Variance value of the link in Setup B when a person crossed the link 10 times.

In contrast with previous experiment with less number of crossings, the variance-based method only able to detect the presence of human across the network links with less accuracy, 71.74%. As per illustrated in Figure 10, variance-based method unable to accurately detect the sequence of affected links when a person moving across the network several times. For example in sample window intervals equal to 7th, 16th, 35th, 41st and 44th, the variance values experience overlapping peaks at the same window interval indicated that two links are effected but unable to identify which link was crossed first, hence variance-based DFL unable to correctly identify the affected area of interest of radio network environment. For example, at 7th sample window interval, the user is expected to move from Area D to Area C, and the variance graph indicates that the user probably located at Area C or Area B since there are increasing in variance values of links N3 and N4 which indicate that the person already crossed both links at the same window interval. The variance-based DFL system produced 28.26% of the result as overlap and false detection.

All experiments conducted show that human movement or any moving objects across the network links will introduce shadowing and multipath effect on the radio signal strength. Both attenuation-based and variance-based DFL results proved that the presence of moving people across network links has cause significant signal degradation. The number of peaks experienced by the attenuation and variance values agrees with the number of crossing in the network environment; however the variance-based method give overlapping peaks result at particular window intervals resulting in false human detection. This proved that localization and detection of human moving in moderate pace across multiple network links is better using attenuation-based and variance-based DFL. However variance-based DFL will give less localization accuracy if the number of crossing is increased.

6 CONCLUSIONS

In this paper, an RSSI-based DFL system has been proposed for elderly care application. The effects of human presence in both moving and static scenarios have been presented and compared between attenuation-based and variance-based method. The result shows that, attenuation-based method able to accurately detect the presence of stationary people compared to variance-based method which unable to detect stationary people in presence in monitored area. Since people living in house always performed daily activities which spend considerable amounts of time without moving, the attenuation-based is more suitable for elderly care application compared to variance-based DFL. In the case of moving people scenario, both attenuation-based and variance-based methods able to localize moving people. The attenuation-based method successfully detects the number of crossing and the sequence of trajectories with 100% accuracy while variance-based only gives 71.74% accuracy. Work is in progress to optimize the network links so that each node can communicate with each other to create more network links that can improve the localization accuracy. Further work will involve exploring attenuation-based DFL system in larger area which might not only focus on localizing, but as well as fall-detection that is very useful in elderly-care application

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