Enhancing the Accuracy of Wi-Fi Tomographic Imaging Using a Human-Interference Model

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***Abstract*— Since the reconstruction process of Wi-Fi Tomographic imaging is an ill-posed inverse problem and due to the unstable nature of the measurements, converting the signal strength measurements into a two dimensional image is computationally expensive. Therefore this research is intended to propose a human-interference model that can be used to enhance the accuracy of the tomographic imaging process while reducing the computational cost. This paper discusses the application of human-interference model to improve the Wi-Fi tomographic imaging, and also the paper includes details about implementation of the algorithm and improved image reconstruction process along with results. The proposed novel methodology uses both regularization and the human interference model to enhance the accuracy of the imaging process.**

***Keywords*— Wi-Fi Tomographic Imaging, Optimization, Human-Interference Model, Sensor Networks**

I. INTRODUCTION

Tomography refers to the technique for imaging physical objects by observing the effect on those objects due to waves passing through them. During Radio tomographic imaging(RTI) the attenuation of physical objects within a wireless network is imaged using the "Received Signal strength(RSS)" measurements. According to this scenario, in order to image the objects within a wireless network, it has been proved that Wi-Fi signals can be used. During the communication of wireless nodes, Wi-Fi signals pass through the physical area of the network. Then the objects within the network area can absorb, reflect, diffract or scatter some of the transmitted signal power.

The tomographic imaging process can be optimized at two stages as, measuring of RSS values and the reconstruction of tomographic image. According to the background study conducted about Wi-Fi tomographic imaging, the main issue that led to conduct this research was, previous researchers have not engaged with applying prior knowledge to the tomographic imaging process to obtain accuracy. They had been highly depend on complex mathematical methodologies such as regularization. I.e. Patwari et al. have proposed regularization methods for radio tomographic imaging [1].

Therefore this research addresses the issue, how to enhance the accuracy of existing Wi-Fi Tomographic imaging using the background knowledge about the process. Human interference model was constructed as a result of that attempt. This research uses **ESP8266** Wi-Fi modules as the nodes in the network and thereby, uses the human interference model to improve the Wi-Fi tomographic imaging. This research also implements an algorithm to enhance the WTI imaging process by using the human interference model. The model was tested in real world experiments to ensure the accuracy.

II. BACKGROUND

This section will provide the theory and the history of radio frequency based localization methods and the background of radio tomographic imaging. Hence, Wi-Fi signals is also a type of radio signals, this research uses same theories that were used in Radio Tomographic Imaging. It is cost effective, accurate, efficient and simple to employ Wireless and Sensor Networks (WSN) s for tomographic imaging.

A. *Passive, Device-free localization(DFL)*

Device-free indoor localization aims to localize people without requiring them to carry any devices or being actively involved in the localization process. But in the Passive Radio Frequency Identification (RFID), for example, the entities being tracked to carry a device that backscatters a signal using an electromagnetic resonance structure. It cannot be considered device-free, although the tag is not actively powered by a voltage source. The terms "tagless" and "tag free" are often used equally with "device-free" [2].

B. *Received Signal Strength Indicator(RSSI)*

Commonly mentioned as the measured signal power, which is the receivers received signal strength calculated by the RSSI circuit. For RSS based localization systems, additional hardware are not required, as most of the sensors already contains a RSSI circuit built-in. Usually, RSSI is measured in decibel(dB).

C. *Linear Formulation*

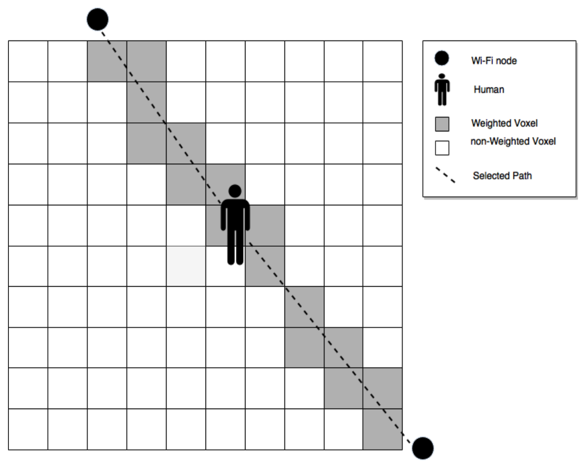

Fig. 1: A visualization of a single link in a Wi-Fi Tomographic Imaging network that travels through the

human obstacle. The dark voxels shows the non-zero weighting for the particular path.

The signal strength $y_i(t)$ of a particular link i at time t is dependent on following variables.

- Pi - Transmitted power.
- S_i (t) - Shadowing loss due to objects that attenuate the signal.
- F_i (t) - Fading loss that occurs from constructive and destructive interference of narrow-band signals in multipath environments.
- L_i - Static losses due to distance, antenna patterns, device inconsistencies, etc.
- $v_i(t)$ - Measurement noise.

Mathematically, the received signal strength of the receiver is described as [3],

$$y_i(t) = P_i - L_i - S_i(t) - F_i(t) - v_i(t) \quad (1)$$

The change in RSSI from time t_1 to t_2 is Δy_i,

$$\Delta y_i = y_i(t_b) - y_i(t_a) = S_i(t_b) - S_i(t_a) + F_i(t_b) - F_i(t_a) + v_i(t_b) - v_i(t_a) \quad (2)$$

By applying $S_i(t) = \Sigma_{j=1}^{N} w_{ij} x_j(t)$,

$$\Delta y_i = \Sigma_{j=1}^{N} w_{ij} \Delta x_j + n_j \quad (3)$$

Furthermore, this all equations can be described in matrix form.

$$\Delta y = W \Delta x + n \quad (4)$$

Where,

$$\Delta y = [\Delta y_1, \Delta y_2, \dots, \Delta y_M]^T$$
$$\Delta x = [\Delta x_1, \Delta x_2, \dots, \Delta x_M]^T$$
$$n = [n_1, n_2, \dots, n_M]^T$$
$$[W]_{i,j} = w_{ij}$$

D. Enhancing Accuracy of RTI

If the result of the tomographic imaging process gives the exact location of the person inside the network region it is the most accurate result. Regularization acts as the main role in enhancing the accuracy of the tomographic imaging process. Other than regularization there are few other methods for enhancing the accuracy such as using channel density [4], using directional antennas and using powerful hardware.

Ossi et al. have proposed a novel approach that can be used to improve the accuracy of tomographic imaging by using the channel density. In this research, they have proved that people can be located with an average error as 0.10 m. This is a simple and an effective way [4].

Wei et al. have proposed that a directional antenna can be used to improve the accuracy of the tomographic imaging. By using directional antennas they have reduced the effect from multi-path propagation. This method will be inexpensive and efficient for energy saving [5].

Zhang et al. have recently proposed a system called WiFi-ID that analyses the channel state information [6]. This extracts unique features that are representative of the walking style of an individual in order to identify that person uniquely. This system gives an accuracy of 93% to 77% from a group of 2 to 6 people, respectively [6].

With respect to all the above studied researches, we can conclude that all those methods are using a high computational power to improve the accuracy. Due to that this research was aimed to implement a way of improving the accuracy while reducing the computational cost.

III. WI-FI TOMOGRAPHIC IMAGING WITH HUMAN INTERFERENCE MODEL

Many pixels are being estimated from relatively few nodes are given as the heuristic explanation for the ill-posedness of RTI model. Multiple possible attenuation images are existing which can lead to the same set of measurement data. As an example if a particular pixel is not crossed by any link in the network, it would result in the same measurement data for every possible attenuation value of the pixel. Therefore the inversion of the problem would be impossible. Regularization introduces additional information into the mathematical cost model to handle the ill-posedness. Previous researchers indicate that regularization can be used to reconstruct images. Any of these methods are not using information from the context. Therefore it can be concluded that the existing regularization process lacks with the knowledge about the context. This research is intended to show how to use information from the context to enhance the accuracy of the image reconstruction.

The proposed network for this research is consisting of 28 nodes. Every node is consisting of a single ESP8266 module. Nodes are communicating in the round robin manner and when one node starts acting as a sender, all other nodes act as receivers. The next sender node is chosen randomly.

In order to build the human-interference model the experiment shown in Figure 2 was conducted by locating a person in between two Wi-Fi nodes and measuring the relevant RSSI values.

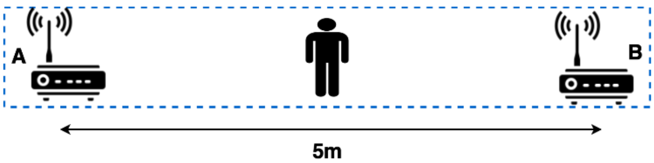

Fig. 2: Illustration of the experiment conducted to build the human-interference model.

A is the sender node and B is the receiver node. In this experiment NodeMCU with ESP8266 Wi-Fi soc were used and they were placed 5m apart from each other. The person was located in the middle of AB direct line-of-sight path. Wi-Fi RSSI measurements were collected from node B. A mean based filtering technique was used for this research and the mean was obtained by analyzing the measurements that were taken during the experiment. By considering all the obtained threshold values, the general human-interference model was built up. The steps of this experiment are illustrated in diagram (Fig 3).

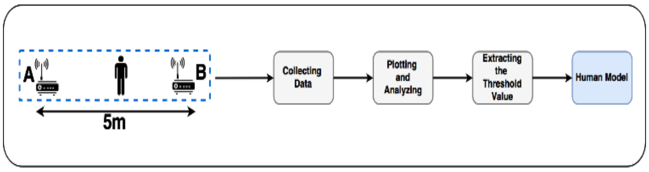

Fig. 3: Flow diagram of human-interference model building process

When Δy is all link difference RSS measurements, Δx is the attenuation image to be reconstructed, n is a noise vector and W is the weighting matrix, link difference RSSI measurement can be written as,

$$\Delta y = W \Delta x + n$$

Each value is measured in decibels (dB). To simplify the notation X and Y are used for Δx and Δy respectively.

$$Y = Wx + n \quad (5)$$

When mean based human-interference model (h_m) is given,

$$\bar{Y} = h_m . Y \quad (6)$$

New equation for image reconstruction can be written as,

$$\underline{Y} = Wx + n \quad (7)$$

As the next step, regularization was used to solve this equation since this is also an ill-posed inverse problem.

Apart from performing the full tomographic imaging process, the human model which is proposed by this research will be used. It will return more accurate results by using the proposed human model before applying the regularization. The diagram (figure 4) illustrates this process as an overview.

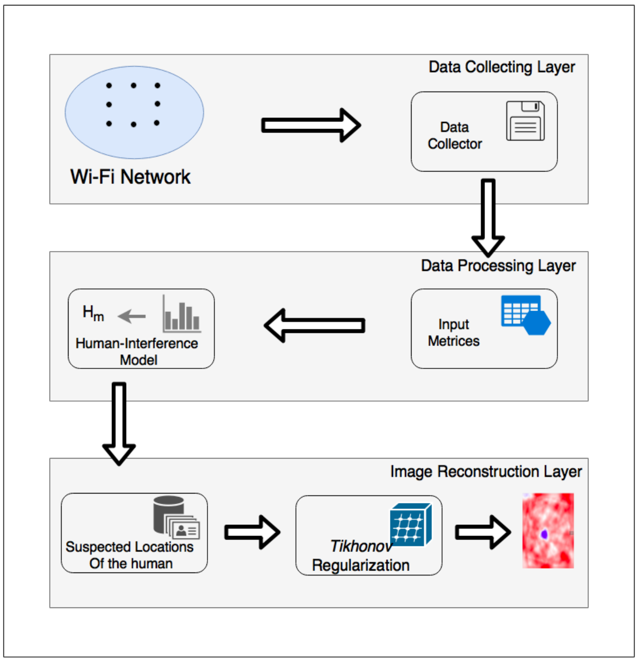

Fig. 4: Flow diagram of overall Wi-Fi tomographic imaging process including the Human-Interference Model.

A. *An Algorithm to enhance Wi-Fi tomographic imaging.*

Given below is the algorithm which was designed to enhance the accuracy of the Wi-Fi Tomographic Imaging process, together with the human interference model.

Algorithm 1 Creating tomographic imaging by using Human-Interference Model

1: Read two input matrices
2: Create the weight matrix
3: **if** *the human-interference model* is given **then**
4: Extract the suspected human location from the weight matrix.
5: Return the resulting matrix.
6: Apply the Tikhonov regularization for the resulting matrix.
7: Reconstruct the tomographic image.

B. *Hardware component*

The Hardware component is consisting with one nodeMCU, one reset button and a LED. When the node is communicating with the access point, LED gives an indication. The reset button is to reset the memory and restart the process. A total of 28 nodes were used for this experiment.

Fig. 5: Hardware implementation of the Wi-Fi node

IV. Experiment

A. *Water bottle experiment*

This experiment was conducted to show that the existence of water bodies will effect on the Wi-Fi RSSI values.

Fig 6: Location of the water bottle within the network.

Two nodeMCU modules were used as the sender and receiver of this experiment. The two nodes were placed 50 cm distance apart from each other. Then a bottle filled with water was located in middle of the LOS path between sender and receiver nodes. The bottle filled with water was considered as the water body for this experiment. Next, RSS measurements were obtained during a time period of 10 minutes [Figure 6]. By analyzing the collected data it was found that Wi-Fi RSSI values were affected by the water body. Therefore it can be concluded that water bodies affects to decrease the RSSI measurements.

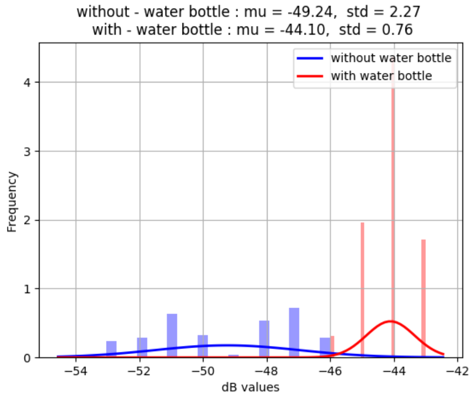

Fig. 7: Effect of the water bottle on the Wi-Fi RSSI values.

B. Building Human-Interference Model

The total percentage of water inside the human bodies varies with age. However, this percentage varies from 50% to 75%. Therefore it can be stated that more than 50% of the human body contains water. Due this conclusion we can assume that the human body has the ability to absorb radio signals due to the presence of water inside the body.

The results received in the two instances where the person is present within the network and when the person is absent within the network, shows a significant difference. The experiment was conducted in a grassy outdoor area. The steps of the experiment are described further during the below section. The Wi-Fi nodes were located 5m apart from each other. At the first phase, RSSI values were measured for the instance without a person within the network. In the next phase, a person was located within the network at the center of the LOS path between sender and transceiver and RSSI values were measured.

Fig. 8: Empty area selected to conduct the experiment on building the human-interference model

Fig. 9: Experiment of building human-interference model located a person in the middle

By analyzing the collected data, a mean based human interference model was buildup.(hm). The graph [10] shows the RSSI measurements after analyzing the data. By using the analysis, the human-interference model was built up.

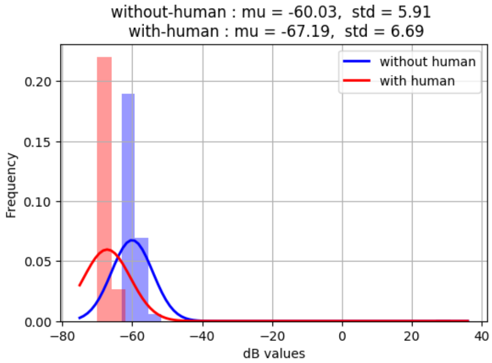

Fig. 10: Effect of the person on the Wi-Fi RSSI values.

C. Wi-Fi tomographic imaging using human-interference model

During this phase, the complete WTI process was evaluated after applying the human-interference model. A grassy outdoor area was selected to conduct the experiment and Wi-Fi nodes were deployed within the selected location. The nodes were supplied with power and made them ready to collect data. The distance between any two nodes was set to 0.5m. The experiment was conducted for a square shapes grid area as a peer to peer network. Design of the network was arranged in a rectangular topology. The first data set was obtained for the instance without locating the person within the network area. (i.e empty environment stage).

During the next step, a person was located inside the network area measured the RSSI values. The person was asked to stand in the locations shown in figure x within the network for a given time period (approximately seven minutes). The ESP would scan for RSSI values in every two seconds. All the data was written to the ESP memory. For a single time period, approximately 150 lines of data were collected. The experiment was conducted for different locations for static standings of the person.

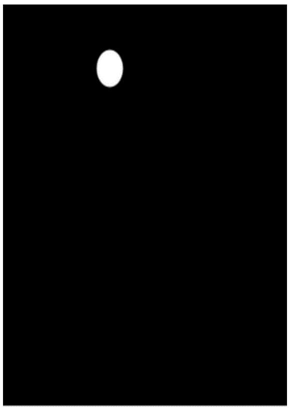

Fig. 11: Location of the person during experiment 1

Then the data set was processed for the human-interference model and the results were obtained. The received results were applied to the Tomographic imaging process and obtained following results [Figure 12].

The bright spot shows the actual location of the person within the wireless network.

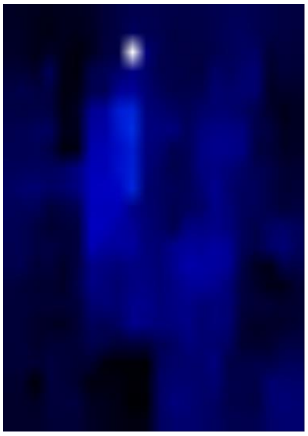

Fig. 12: The optimized result received by applying the human interference model for experiment 1

V. Evaluation

This section is intended to evaluate the results obtained during the research. Since this is an image based research, the most suitable way to evaluate would be a user evaluation. But, due to the practicability, the results are evaluated based on a mathematical approach. Since the final result of the Wi-Fi tomographic imaging process is an image, the following three methods are followed to evaluate the results.

1. Image similarity by histogram method [7]

Within the image processing context, the Histogram of an image refers to a plot of pixel intensity values. This graph plots the number of pixels in an image at different intensity values of that image.

2. Image similarity by hashcode method [8]

Average hash algorithm is a simplified version of a perceptual hash.

3. Image similarity by root mean square error method [9]

In statistics, the Mean Squared Error (MSE) of an estimator refers to the measurement of the average of the squares of the errors or deviations (the difference between the estimator and what is estimated). It is a risk function, corresponding to the expected values of the squared error loss or quadratic loss. This difference occurs due to the randomness or due to the estimator doesn't account for information that could produce a more accurate estimate.

A. Evaluation for experiment 1

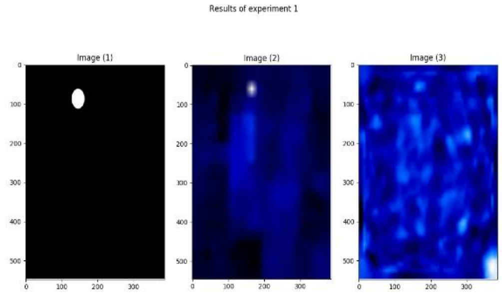

Fig. 13: Evaluation process of the experiment 1

We received the following measurements for experiment 1.

Method	Ground truth image Vs. non-optimized method	Ground truth image Vs. optimized method
Image similarity by histogram method	390.68	352.06
Image similarity by hash-code method	1282.0	1313.0
Image similarity by root mean square error method	7168.24	6523.65

TABLE I: Evaluation matrix for experiment 1

VI. Conclusion

In this paper, we brought background knowledge to the Wi-Fi tomographic imaging is a new concept and it was achieved with Human-interference model. As demonstrated in background section, existing accuracy enhancement methods are totally hardware based and uses a considerable amount of computational power. But this paper proposed a strong statistical methodology to enhance the accuracy of WTI. First, the human-interference model for Wi-Fi was developed. This is the main contribution for this research domain. Then the human-interference model was integrated with existing WTI.

To address the research problem, different approaches were tried out. Since this research problem is a kind of optimization problem, during the first stage, constrained optimization solution based on background knowledge was explored. But it misguided the results and then constraint filtering approach was tried out. Then the statistical human-interference model for this approach was build.

A. Limitations

During the initial stage of the research it was planned to conduct the research for indoor environments. But with the identification of unwanted noise in side indoor environments (multi-path interference), the experiments were conducted in outdoor environments during the research.

Due to the less accuracy of the results, the number of nodes used for the experiments were increased from 15 nodes to 28 nodes.

At the beginning of the research it was planned to conduct the research using a single person within the selected network area. Therefore most of the experiments were conducted using a single person. During a later experiment, it was able to locate two persons inside the network to conduct the experiment.

VII. FUTURE WORKS

Since the accuracy decreases with the number of nodes, 28 nodes were used for this research experiments. Therefore the requirement of a method to reduce the number of nodes is needed while keeping the same level of accuracy. For all the experiments of this research, nodeMCU modules were used as the Wi-Fi senders and receivers of the network. Therefore the requirement of investigating an approach to use the existing Wi-Fi routers to replace the nodeMCU modules for the tomographic imaging process is available. This will lead to implement the concept of Smart home monitoring in the future.

Timeliness of which information is delivered has become a crucial factor to human life style at present. Therefore the tomographic imaging also requires to be met with the real-time aspects. Next step of this research will expand towards implementing real-time Wi-Fi tomographic imaging using human-interference model.

VIII. ACKNOWLEDGMENT

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