Decimeter Level Indoor Localisation with a Single WiFi Router using CSI Fingerprinting

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***Abstract*—The accurate localisation of multiple objects and people in indoor environments is challenging. The problem is of immense importance in the context of Internet of Things (IoT) applications. In many scenarios, there is a high density of people and objects which need to be spatially and temporally tracked. As IoT applications find increasing use not only in industrial applications but also in novel areas such as healthcare in the hospital settings, indoor localisation challenges need redress. The paper addresses a novel technique for indoor localisation for a resolution of 10 cm for Line-of-sight (LoS), and Non-Line-of-sight (NLoS) setup. The received signal strength indication (RSSI) based on WiFi signal is thoroughly studied in the past and has offered localisation solutions, yet it is highly sensitive to temporal and spatial variance due to multipath effect. The Channel state information (CSI) signal transmitted from WiFi hardware offers both space and time information, remains relatively stable with multipath propagation and interference, thereby the signal is considered highly suitable for designing localisation techniques with precision. The proposed solution is designed on an open source hardware, and CSI fingerprinting database for 100 locations that are spaced 10 cm apart for line-of-sight (LOS) and Non-line-of-sight (NLOS) configurations are acquired to generate classifier models using different Machine Learning algorithms. Random forest classifier model showed localisation results of 93.15% and 98.01% for LOS and NLOS respectively, for a resolution of 10 cm, which is reported for the first time. The design and technique can be further extended to various applications including patients localisation in dense waiting room of hospitals, home medical care, and other multiple tools localisation in an industrial environment using existing WiFi router infrastructure.**

I. Introduction

Outdoor localisation systems like GPS have had a profound impact on the world, benefiting mankind in navigation, location based access, controlled security, distress handling, and many such significant and critical applications. Satellite based positioning, Light detection and ranging (LIDAR) based tracking and other standard methods used in outdoor localisation are not suitable for indoor settings. The difficulty in indoor localisation has resulted in techniques with difficult to fulfill requirements and has hindered applications. Industry 4.0 which is the driving force for IoT adoption also faces significant challenges in tracking people and material in confined closed environments.

Healthcare is one of the upcoming areas where IoT practises are expected to be adopted [1], [2]. The changes in healthcare owing to the novel Coronavirus pandemic has ensured that the changes would be implemented sooner than later. Large hospitals have multiple areas where indoor tracking is of vital importance. Instances include out-patient departments, especially in Indian Government-funded hospitals where crowding is a norm. Conventional crowd control measures largely have been noted to be ineffective. The pandemic situation has necessitated looking at novel methods for indoor tracking for crowd control. An Intensive care unit is another area where a patient is surrounded by numerous devices which need to be tracked. In tracking these devices, the physical presence is of the same importance as the data which is received or processed by the device. Examples include Injection-Pumps, Ventilators, Mobile Vital-signs-monitors such as Pulse-Oximeters etc. Most modern operating rooms have a multitude of equipment which are used during various surgeries. Cardiac surgeries, surgeries on brain and spinal cord ensure that there is wide circulation of material and people both within the operating room as well as the operating rooms and stores. In all scenarios listed here, the existing practises involve personal intensive methods of documentation which is primarily contact based. IoT applications when implemented would ensure seamless non-contact data transfer which is the need of the hour. The implementation of IoT frameworks in turn necessitate accurate and high resolution Temporal-Spatial localisation which is consistent, repeatable, and seamless with existing technology.

In addition, the indoor localisation is highly useful in other applications such as fire rescue operations in large shopping malls. Given the vast demand, a highly accurate and precision based indoor localisation is immediately needed to serve the society. Simultaneously realizing indoor localisation using existing technology seems a more practical approach, instead of developing a novel device and equipment for the same, where additional infrastructure cost and time to install is needed [3].

The primary challenges for indoor localisation ranges from lack of GPS signals reaching indoors, to unpredictable wireless propagation conditions [4]. Indoor localisation using inbuilt sensors in the smartphones such as Inertial Measurement Unit (IMU), light, and acoustic sensors are attempted [5] in the past. However these sensors data have biases from the sources of signals, or require specific indoor designs such as LEDs or optical sources for light-based-localisation, and similarly narrow space indoors for acoustic sensors based localisation to be implemented [5]. The standalone IMU sensors do not offer accurate localisation measurements. WiFi based RSSI fingerprinting is an alternate technique and is highly employed owing to its features including ease of availability,

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privacy protection, and low deployment cost [6]. It offers better localisation results when compared to WiFi triangulation technique. However RSSI suffers from multipath interference, and shadowing effects in a complex wireless environment [7], [8]. Hence in the recent past, many have resorted to CSI signal for precise indoor localisation [9]. CSI signals are considered highly stable and consists of rich information that characterizes wireless information in detail [3]. The CSI embeds two features: physical layer power feature, and channel response that remains undeterred to multipath reception, and temporal dynamics [7]. The CSI based localisation was introduced in [10], with few of the machine learning techniques, however the classification accuracy was reported for a minimum of 1 m localisation. An improved classification algorithm applied on CSI phase information was reported in [11]. Multipath CSI phase information was utilized to fingerprint and further localize the user as stated in [12]. A regression technique was applied on the CSI phase driven classifier results to obtain localisation results [13]. A linear transformed phase calibrated data was applied to neural network and localisation was attained [14]. However in most of the cases reported on CSI phase driven localisation, the accuracy is low due to the highly fluctuating nature of phase parameter [3]. Meanwhile effective CSI amplitude from sub-carriers were extracted and indoor localisation propagation model was also studies. The localisation coordinates of the target are estimated by trilateral method [15], which provided results for *1m* resolution, and accuracy dropped to 50% for *0.5m*. The technique is not useful for close proximity localisation. In an other study, a probabilistic model was adopted to map the observed CSI with the stored fingerprints, and around 1 m localisation accuracy was effectively achieved using more than 3 access points [16]. 89% accuracy in a grid like spot structures of dimensions $1m \times 1m$ was localized using the mixture of Gaussian distribution of channel response across reference points. A system was designed from off-the-shelf Intel 5300 cards to establish the localized signature [17]. A similar yet open source hardware independent of protected design will be highly useful for application developers. A K-means clustering technique was applied in the past [18], to determine localisation for a resolution of 1.26 m. Random forest driven indoor localisation for LoS, and NLoS were implemented using four routers to a resolution of 1 m, with high accuracy [19]. A triangular Centroid algorithm was applied on CSI amplitude signature acquired from narrow band-IoT device [20]. The localisation error obtained from triangle Centroid algorithm was further optimized by conjugate gradient method, and much stable localisation results were obtained. The above CSI methods employed were reported for a resolution range of 1 m, and in addition, the hardware was custom designed on a commercial chipset, thereby inhibiting other designers and developers. Most of the indoor localisation methods employed multiple access points. The paper proposes a indoor localisation solution using CSI fingerprinting method, by employing the widely available and open source Raspberry Pi single board computer. The paper demonstrates a design that sniffs CSI signal from the single WiFi router and establishes fingerprint database consisting of pre-processed CSI amplitude for a resolution of 10 cm and above. Further different Machine learning techniques including Support Vector Machine and Random Forest Classifier was used to determine the localisation results for resolution of 10 cm for LoS and NLoS settings.

II. System Design

As WiFi signals travel through an indoor environment, they are affected by multipath effect, Scattering, Fading, and Power Decay, among other phenomenon. Channel State Information (CSI) describes the combined effect of the phenomenon for WiFi signal as it propagates from the transmitter to the receiver. Localisation by CSI fingerprinting is achieved by collecting CSI data and comparing it with a database of CSI samples whose location is stored in the database. Raspberry Pi 3B+ was chosen because of its widespread availability, affordability, and capability of forming 40 MHz WiFi links. The default Broadcomm firmware does not allow acquisition of CSI data, so Nexmon framework [21] was used to patch a modified firmware [22] to enable CSI collection. The patch allows CSI data to be embedded in a UDP stream which was captured using *tcpdump* utility in a .pcap format. WiFi functionality of the chip is not accessible while collecting CSI data, so an Ethernet link was used to communicate with the Raspberry Pi. The device was mounted on a stand as shown in the Fig. 1, that elevates the acquisition system to 30 cm above ground and measures CSI for all packets transmitted by the router. The stand design is imperative to maintain 30 cm clearance above the floor to minimize capturing of radio waves reflections from the surface, and at the same time allows to maintain a steady position for the device for the fingerprinting activity. A router of TP-Link Archer C20 acting as a Wireless Access Point, operating on 802.11ac, and channel 36 with a 40 MHz bandwidth was deployed for the fingerprinting and localising experiments. Access Points created with hotspot feature of mobile phones showed increased noise in CSI signal when compared to WiFi router device. Additionally, the WiFi router is a part of general infrastructure design in today's large campus, hence validating experimental results using WiFi access point is close to real life scenario.

III. Experiments and Results

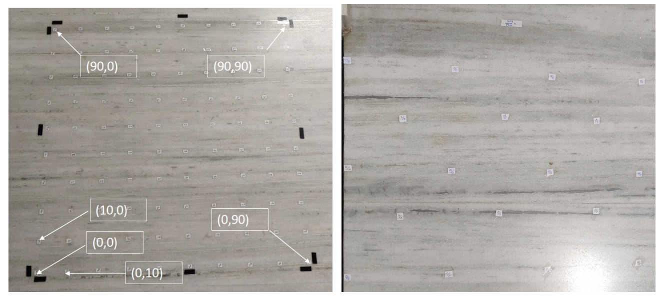
CSI data was collected in both Line-of-sight (LoS) and Non-line-of-sight (NLoS) locations, which are shown in Fig. 2. The LoS site and the router were about 50 cm apart with no obstructions in between, while the NLoS site was in a neighbouring room with a concrete wall and few furniture in between. The furniture position was not changed through the fingerprinting and validation experiments. To reflect real-world results, all the experiments were done in a residential setting with people present and moving. 12000 samples of CSI were collected at each of the 100 fingerprint locations under LoS settings and 18 fingerprint locations in NLoS setting, that are spaced 10 cm apart. CSI data has both Phase and Amplitude information, but the former was considered highly

Fig. 1. A picture showing Raspberry Pi mounted on a wooden stand, and is powered with a USB cable.

sensitive, and hence was discarded, retaining the absolute Amplitude of CSI for fingerprinting. The 40 MHz WiFi link contains 128 sub-carriers, including 108 Data sub-carriers, 11 Guard sub-carriers, 3 Null sub-carriers, and 6 Pilot sub-carriers. Guard and Null sub-carriers are not modulated while the Pilot sub-carriers use a different modulation than the Data sub-carriers, so CSI from these three sub-carriers was filtered away. An image of CSI data post removal of unused sub-carriers is shown in the Fig. 4. CSI is sensitive to changes in the channel, and as such, movement and activity in the indoor environment add noise to the data. Hence a simple yet effective method to de-noise the CSI data was employed. At each location, Centroid of the 12000 CSI samples was calculated and $\frac{1}{3}^{rd}$ of the samples farthest from the Centroid in 108-dimensional Cartesian-distance were considered outliers and were eliminated. Every 4 consecutive samples of the remaining $\frac{2}{3}^{rd}$ were averaged to yield 2000 samples with an improved noise level. The de-noise processed CSI data was considered as fingerprints for all the 100 LoS locations, and 18 NLoS locations mentioned above.

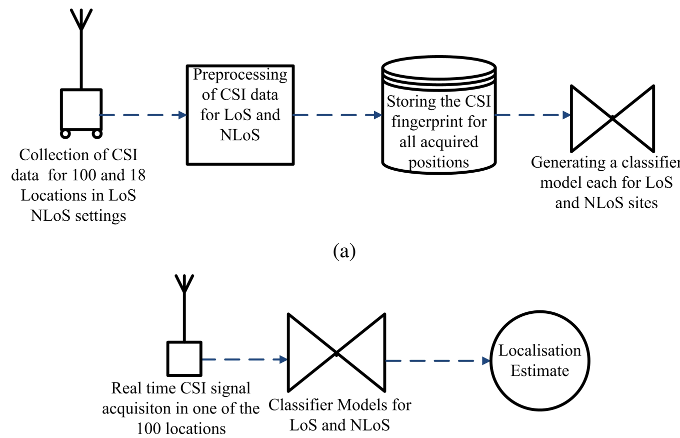
A framework showing the pre-processing of CSI data including de-noising, and few sub-carriers removal was used to train classifier model and testing, and the same is shown in Fig. 3. In our experiments, a model was developed each for LoS and NLoS sites. 80% of the de-noised CSI data was used for training and was tested against the remaining 20% samples. Note that 20% test data represents 40,000 pre-processed de-noised CSI samples for LoS, and of 7,200 samples for NLoS locations.

Each of the classification techniques: Gaussian Naive Bayes classifier (NBC), Support Vector classifier (SVC), Decision Tree classifier (DTC), and Random Forest Classifier (RFC)



(a) (b)

Fig. 2. Snapshot showing CSI data collection points at (a) line of sight position, and (b) non line of sight position.



(b)

Fig. 3. Diagram showing the system framework for (a) Training, and (b) Testing of CSI fingerprinting based localisation.

were used to generate a model at three resolutions: 10 cm, 20 cm, and 40 cm in both LoS and NLoS conditions. The default classification parameters for each of the classifiers with Scikit-learn version 0.23 were used. The default Radial Basis Function (RBF) kernel and Regularisation Parameter of 1.0 was used in SVC. The RFC model was trained using 20 estimators. For every classifier, a confusion matrix was generated from testing against 20% of the samples and was used to calculate accuracy and error statistics. The Figures 6, 7 show that SVC and RFC yield the highest accuracy and lowest mean distance error for 10 cm resolution. Mean distance error reported is the average Cartesian distance between the classified location of a sample and its actual location, across the test samples. Accuracy and mean distance error for SVC, and RFC for three different localisation resolutions under LoS and NLoS configurations are reported in Table I. RFC and SVC showed high accuracy for NLoS when compared with LoS configuration. In *LoS*, the CSI fingerprint at each location consists of two types of signals received from the router: direct path signal, and reflected Multipath signal. The direct path remains strong, as it covers less distance, and signal strengths drops with square of distance. In LoS, the direct path component dominates the CSI signal leading to

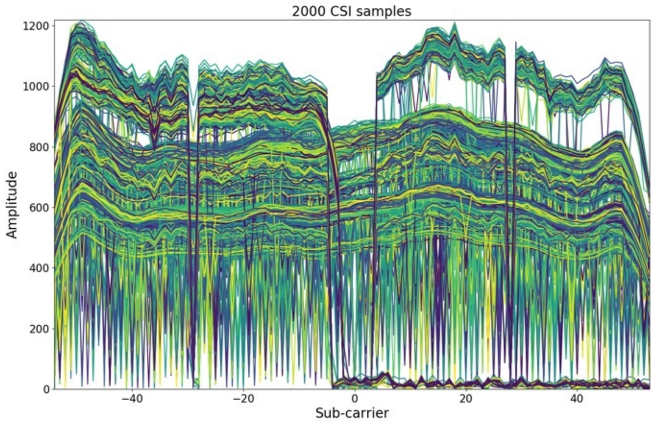


Fig. 4. CSI signal post removing Null and Pilot sub-carriers in one of the LoS position.

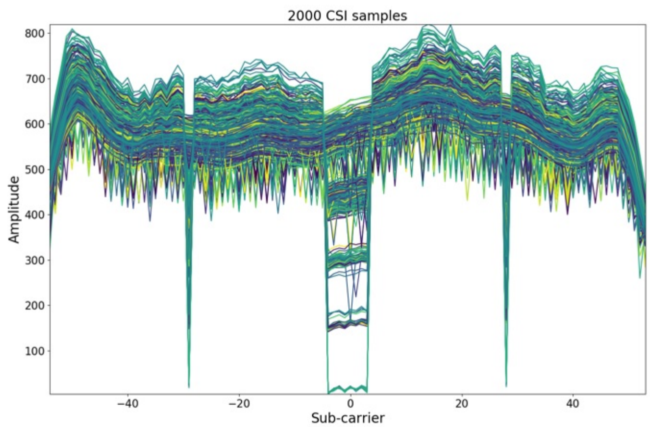


Fig. 5. De-noised CSI signal in one of the LoS position, which is fingerprinted and further employed for developing classifier model.

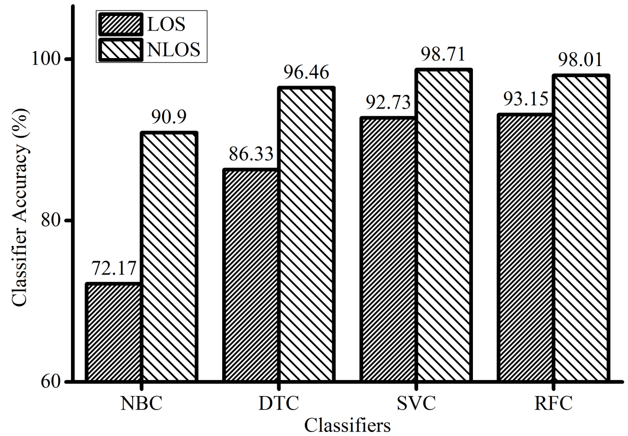


Fig. 6. Classification accuracy at 10 cm resolution for Naive Bayes (NBC), Decision Tree (DTC), Support Vector (SVC), and Random Forest (RFC) classifiers.

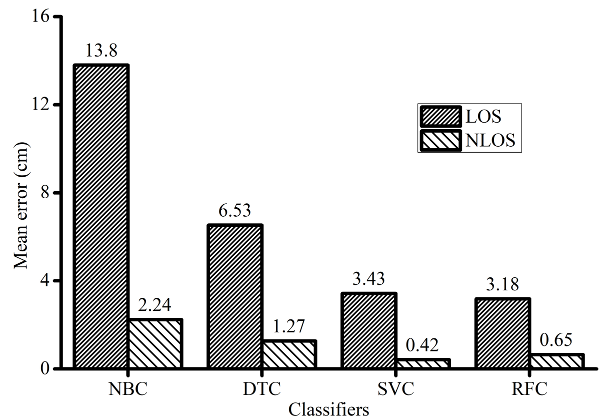


Fig. 7. Mean Distance Error (cm) at 10 cm resolution for Naive Bayes (NBC), Decision Tree (DTC), Support Vector (SVC), and Random Forest (RFC) classifiers.

less signal variance between neighboring localised points. In NLoS, only the reflected signals are present, offering distinct signal strength between neighboring localised points due to the reception of signal from different multiple reflective paths. The distinct signal strength offers high accuracy in NLoS configuration.

Temporal data fusion was used to further improve the localisation accuracy. By classifying 5 consecutive de-noised CSI samples and selecting the most frequently occurring classification as our final prediction, the localisation accuracy was boosted to 99.96% for both SVC and RFC classifiers in both LoS and NLoS scenarios.

The final localisation accuracy obtained from temporal data fusion technique can be calculated using simple probability techniques and is expressed as shown in the equation 1, where P_c is the model classification accuracy, and P_{final} is the final localisation accuracy. Graph in the figure 8 is plotted from equation 1 which shows the localisation accuracy obtained from temporal data fusion versus model classification accuracy. To summarize the advantage of temporal data fusion method, 100 samples per second were acquired by the designed client device, from which $\frac{1}{3}^{rd}$ are filtered away for being noisy, remaining with 66 samples. Every 4^{th} samples are averaged to further render noise free CSI signal. Finally temporal fusion of 5 samples were performed to achieve enhanced localisation to seek 3 predictions in a second with an accuracy of close to 99.96% for 93.15% accuracy obtained from RFC for 10 cm localisation in LoS condition.

$$P_{final} = 1-((1-P_c)^3 \times P_c^2 + (1-P_c)^4 \times P_c + (1-P_c)^5 \times P_c^0) \tag{1}$$

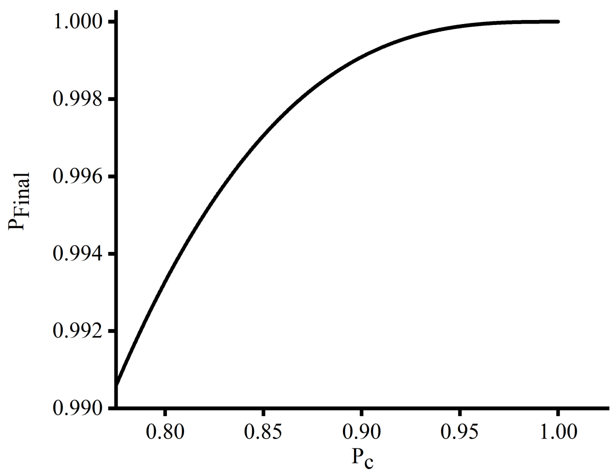


Fig. 8. Localisation accuracy using Temporal Data Fusion versus Model classification accuracy plot shows the extent of accuracy improvement using data fusion.

TABLE I
MEAN ERROR AND ACCURACY FOR 3 DIFFERENT RESOLUTIONS.

Classifier	Resolution	LoS		NLoS	
		Mean-error	Accuracy	Mean-error	Accuracy
SVC	10 cm	3.43 cm	92.73%	0.42 cm	98.71%
	20 cm	0.79 cm	98.70%	0.49 cm	98.50%
	40 cm	1.06 cm	98.56%	0.77 cm	98.09%
RFC	10 cm	3.18 cm	93.15%	0.65 cm	98.01%
	20 cm	0.53 cm	98.95%	1.01 cm	97.29%
	40 cm	0.27 cm	99.53%	1.02 cm	97.47%

IV. CONCLUSION

CSI signal fingerprinting method for precise localisation using open source hardware platform is demonstrated successfully. The CSI fingerprinting method using a single router showed an accuracy of more than 98% in NLoS conditions, and 93.15% in LoS conditions using Random Forest Classifier for a resolution of 10 cm. The higher accuracy in NLoS compared to LoS conditions is attributed to the higher dynamic range of NLoS signals which result in more distinct fingerprints. The fingerprinting process although is vulnerable to the changes in the positioning of interiors, but for routine non structural changes, the proposed localisation method offers significant value addition, considering that the technique employs an existing WiFi infrastructure, and such a localisation technique would vastly improve the push of IoT applications in novel areas such as healthcare.

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