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Device Free Localisation Techniques in Indoor Environments

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ABSTRACT

The location estimation of a target for a long period was performed only by device based localisation technique which is difficult in applications where target especially human is non-cooperative. A target was detected by equipping a device using global positioning systems, radio frequency systems, ultrasonic frequency systems, etc. Device free localisation (DFL) is an upcoming technology in automated localisation in which target need not equip any device for identifying its position by the user. For achieving this objective, the wireless sensor network is a better choice due to its growing popularity. This paper describes the possible categorisation of recently developed DFL techniques using wireless sensor network. The scope of each category of techniques is analysed by comparing their potential benefits and drawbacks. Finally, future scope and research directions in this field are also summarised.

Keywords: Device free localisation; Wireless sensing; Compressive sensing; Machine learning; Radio tomographic imaging

1. INTRODUCTION

The conventional method for localisation of an object that prevailed over a longer period of time was device based localisation. A device is equipped with the target for running the localisation algorithm. Various active based localisation techniques of high popularity are global positioning system (GPS)[1,2], radio frequency (RF) based localisation[3], infrared (IR) based localisation[4], and ultrasonic based localisation[5]. But in certain applications like elder people tracking, invader tracing; the target cannot be expected to hold the device during tracking. In such situations where the subject is non-cooperative, device free localisation (DFL) technique is the ultimate alternative in which, the target need not equip the device for getting localised.

Apart from this constraint, equipping GPS receivers in the target is expensive and is not a permanent solution for indoor localisation because of its line-of-sight requirement. Radio frequency signals are most penetrating type in the electromagnetic spectrum and are the widely used technique in a cluttered indoor environment even though RF signal is affected by interferences in the medium. RF signal works well in a smoky or dark scenario and do not demand a line-of-sight path. In infrared based localisation, light intensity is taken as a measure for target position estimation which is also prone to distortion. A sonic output is highly influential to the surface which it hits and requires additional hardware. All these problems head towards the necessity of DFL it is easy to use, re-deployable, and remotely configurable with minimum delay.

Due to the convenience offered, mobility, flexibility, cost-effectiveness, and high-performance level, wireless technology has gained widespread importance in the field of communication. Wireless sensor network or WSN is an autonomous group of spatially distributed, highly organised, collaboratively working, and environment sensing network. Compared to wired techniques, WSN has low installation and maintenance cost. It can be readily reinstalled in any area of interest and that too as many numbers of nodes depending on applications. After detecting the needed parameter, the data is passed through the network and to a base station for its processing and interpretation. Thus, DFL using wireless sensor network will definitely revolutionise automation and smart technology by combining their respective positive traits.

Nowadays location estimation of an entity is an interesting area of research and so as in applications such as home automation, security[6], health care[7], military and security applications, elderly care applications[8,9], medical care assistance[10,11], etc. Various surveys related to DFL algorithms, techniques and challenges are done till date in which, two researchers reported emerging applications of DFL in wireless sensor networks through their different modalities used for localisation of target[12]. A comparison of recent techniques available in indoor localisation was done by Deak[13] and Pirzada[14]. Pirzada[15] also conducted extensive survey depicting the popular techniques in DFL system. An analysis of device free passive localisation system in indoor was proposed by Kivimaki[16] in the same year. From the literature, it is projected that DFL is a promising efficient target localisation system particularly, for indoor environment.

The main highlights of the paper are listed as follows

- The recent technological developments on device free classification are assessed by us in this paper for

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categorising techniques used in DFL

- Comparison among these categories is also made based on these recent literatures for analysing the future prospects in this field
- The comparison within these categories is also performed for identifying the appropriate techniques to be used in different scenarios.

Thus, the paper gives an overview of the concept of DFL and evolution of DFL using wireless sensor networks.

2. EVOLUTION

Location related information is very important for indoor based human detection applications. There are many techniques available in indoor localisation which is broadly classified as device based and DFL methods. Device based localisation is further classified as smartphone based and tag based, depending on the device the target is carrying[17]. If it is a smartphone based, localisation of the target can be easily done with its inbuilt modalities like Wi-Fi, bluetooth, microphone, FM radio, etc., thereby removing the need for extra hardware. The same function is performed by infrared, ultrasonic, RFID, Zigbee based tags but with specific hardware. Even though some modalities may not exist in smartphone they are categorised under smartphone type, based on their attributes to be used in such setup.

Indoor localisation cannot be effective in device based localisation due to the infrastructure expense incurred during target localisation. A device cannot be held by the target for the so-called specific applications. Recently, DFL has emerged as an important technique for attaining these goals.

The main highlight of this technique is that the target need not carry the device involved in running the localisation algorithm which is difficult in certain situations. Moreover, DFL set up easily blend with any environment as no extra hardware is required for its installation for different environments. In DFL, the various modalities used are ultrasonic, infrared, RFID, wireless sensors, Wi-Fi etc.

Before analysing more into DFL, it is necessary to know about different techniques available for device assisted and DFL. A summary of the existing techniques of both categories is as shown in Table 1.

2.1 Why Device Free Localisation in Wireless Sensor Networks?

The tremendous growth in localisation systems together with advancements in wireless communications has motivated the research directions in location estimation of target especially human. The preliminary concept of WLAN based DFL was introduced by Moustafa Seifeldin[18].

Wireless sensor network is a radio frequency (RF) based autonomous network comprising spatially connected sensor nodes that sense any physical phenomenon or parameter. The deployed sensor nodes co-operatively work together to obtain a reliable data out of the network for assessing the location of the target present in the network. The sensor node comprises a microcontroller, transceiver, communication interface, power supply and memory and works in ISM band. So, standardisation is an added advantage of a wireless sensor network. If the spatial information is known correctly, accurate interpretation of data is possible through appropriate deployment of sensor nodes to the event concerned. The decreased size and price of sensor nodes have even aggravated research interests in WSN localisation. Apart from size and price, the prominent features of WSN are simplicity, low maintenance, reliability and security. All these prospects have revolutionised DFL in wireless sensor network.

2.2 Modalities in Device Free Localisation

Radio frequency based communication is the preferred approach in wireless sensor network applications; because of

Table 1. Comparison between device free and device based localisation

Device based localisation				Device free localisation	
Smart phone based		Tag based			
Technique	Modalities used	Technique	Modalities used	Technique	Modalities used
Camera	Image recognition, computer vision based, LED	Ultra wideband	TOA,TDOA	Camera	Pattern recognition approach, image recording.
WiFi	AOA, TOA, RSSI, CSI	Ultrasonic	TOA	Ultra wideband radar	Finite difference time domain (FDTD), round trip time
Inertial sensors	CompAcc, Indoor Nav	Infrared	-	Ultrasonic	Echo recording, door jamb
Acoustic	TOA , TDOA	RFID	RSS proximity, Phase based	Infrared	AOA
FM Radio	RSS	Wireless Sensors	Doppler shift	RFID	Motion event detection, tomographic imaging, reflection tracking
Bluetooth	TDOA, RSS	-	-	Wireless Sensors	RSS, machine learning, TOF, radio tomographic imaging (RTI)
Cellular	GSM, CDMA, LTE, OTDOA	-	-	WiFi	RSS, MLE, CSI
-	-	-	-	FM	Average amplitude, Average magnitude squared, root of amplitude mean squared.

which it is called as ‘RF sensor network’. The wireless sensor network comprises a group of sensor nodes that measure received signal strength between link connecting any two nodes. When a person is present, the nodes obtain the change in signal values specifically received signal strength index (RSSI) from all the nodes and process the data using a suitable algorithm for identifying the exact position of the target. Other parameters under consideration for DFL are time of flight of the signal, Doppler effect and channel state information. The measurement of RSSI values is found to be more easy and promising as most of the commercially available wireless products have that facility. Thus no additional hardware is required. As the target occupies very less space compared to wireless sensor network, very few links get affected and data acquisition and transmission is not so costly as well as complex. Moreover, RSSI values avoid privacy concerns in opposition to cameras. However, accuracy of RSSI based method is highly dependent on the complexity of its environment.

2.3 RF Sensor Networks-based DFL: An Overview

With the virtue of the penetrating power, RF waves pass even through walls or non-metallic structures. Unlike other modalities, RF based DFL neither require any light support during night or in smoky environment nor it requires target equipped tag assistance. The identification and tracking of the subject concerned can be detected based on attenuation of received signal strength in 2.4 GHz band. This is because almost 70 per cent of human body comprises water that is capable of absorbing and attenuating any RF signal at 2.4 GHz.

DFL in wireless sensor networks is further classified[19] as RF fingerprinting, RF grids, RF tomography, and RF backscatter depending on the techniques used to localise the target. In RF tomography, a radio image of the target is generated and subsequent shadowing model reconstructs the RF image of the field or calculate the position coordinates of the target directly through compressive sensing. Radio grids make use of grid arrangement of transceivers to obtain the fluctuations of the signal strength as a measure of identification of the target. In radio fingerprinting a radio map is generated in offline positions for certain predetermined locations. Later in online phase, the accurate coordinates are identified after analysing the fingerprints in offline phase. In RF backscattering method, the devices are communicated by means of ambient RF scattering i.e. by reflecting signals back to their origin.

Most of the researches in DFL has been carried out with suitable experimental setup particularly in indoor and at times in outdoor environment. The setup mainly comprises sensor nodes, power supply, PC, interfacing units working in the range of 2.4 GHz frequency for human detection and analysis is made based on attenuation caused, time delay in the received signal, channel state information etc. DFL measurement based on RSSI values and comparison of smoothing algorithms used were described by Deak[20]. DFL based experimental test bed for human detection was developed and explained by Fink[21].

3. DEVICE FREE LOCALISATION: TECHNIQUES AND CLASSIFICATIONS

In DFL, for any environment comprising wireless sensor nodes, the position of the stationary or moving target can be detected by suitable DFL techniques by understanding the signal strength variations across transceiver links. The algorithms are also classified as attenuation based and variance based[8] on the basis of RSSI variations with human presence.

This section highlights various DFL techniques existing in different scenarios. We have attempted to classify these DFL techniques into statistical, compressive sensing, machine learning and radio tomographic imaging from recent literatures[22-46]. The literatures under review are classified into these DFL techniques represented in the form of a tree diagram followed by detailed explanation (Fig. 1).

3.1 Techniques based on Statistical Methods

The classification of DFL techniques are made based on the methods applied in positioning a target in DFL. The statistical methods are those that are applied to stochastic or random processes, where mathematical models, concepts, formulas especially statistical parameters are used to analyse the random data. The parameters measured are average distance error, tracking error, root mean square error, probability distribution function, cumulative distribution function etc.

Patwari and Wilson[22] derived statistical models that accurately map RSSI variations to the position coordinate of the target with respect to the transceivers. Multi path channel model that incorporates fading and total estimated power (ETAP) due to scattering and reflection was also made as a measure of location of the target. Highest variance was observed at midpoint position of target. Future work is to verify the performance of the model in various cluttered, complex

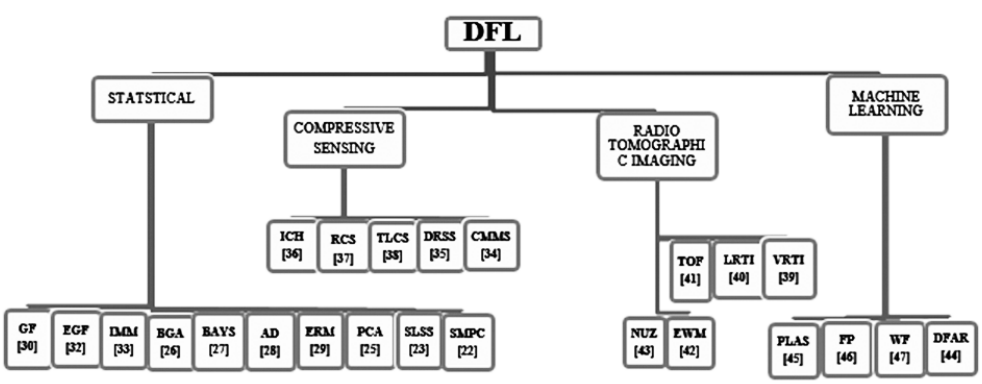

Figure 1. DFL techniques: A tree diagram.

and non-complex real time environment and thereby effective tracking of the target.

Wilson and Patwari[23] proposed a statistical inversion based received signal strength device free localisation (RSS-DFL) model in a static and dynamic environment with better accuracy and robustness. A skew Laplace likelihood estimation model defined by posterior distribution is developed for identifying the state space coordinates of the static or movable object using sampling importance resampling technique. The mean error after 20 iterations for static target was found to be 0.83 m and for moving target it was less than 0.9 m. Development of advanced particle filter technique for better accuracy is still an open challenge for yet more complex scenarios like multiple entity tracking.

Chen[24], *et al.* proposed an energy efficient probability based detection of moving targets in wireless sensor network scenario by developing graph theory based trap coverage. A probabilistic transmission control protocol (PTCP) was also developed for proper scheduling of sensor nodes so as to make the sensor network energy efficient. The performance of the PTCP protocol design was assessed by comparing with trap cover optimisation (TCO) and Randomised Independent Sleeping Scheme. PTCP was found to be energy efficient and of better lifetime when compared to other two protocols. PTCP protocol activates less number of sensors and so average detection probability was found to be lesser than the threshold value. The performance of PTCP was theoretically analysed and was found to be a best choice in worst case scenarios.

Zhang[25], *et al.* proposed, a dynamic model for assessing the RSSI variations for different wireless sensor network scenarios thereby accurately tracking single and multiple targets. For single target tracking, three tracking algorithms such as best-cover algorithm, midpoint algorithm, and intersection algorithm were implemented over the proposed model for assessing their performance. Multiple target tracking was analysed using probabilistic cover algorithm for easy detection of number of objects and their accurate location in a given region of interest with reduced latency. The performance of model equipped with best-cover algorithm was found to be better especially in terms of accuracy and average tracking error at border areas for single target detection. Proper tracking of closely placed multiple targets and sensor deployment in an irregular topology network is an open problem in this area.

Wang[26], *et al.* proposed, a Bayesian grid approach (BGA) based DFL as a robust localisation estimation technique with low computational cost. The proposed approach utilises the information of target affected links, preceding information in previous estimation along with constrained information in non-shadowed links. The performance of proposed BGA was compared with regularisation based RTI and compressive sensing based RTI where tracking error reduced by 60 per cent and 50 per cent, respectively. The technique was also compared with BGA model with absence of prior information and BGA with absence of infeasible region concluding that the average tracking error of BGA reduced by 11.9 per cent and 4.3 per cent, respectively. The overall execution time of BGA is only 1.5 ms indicating BGA as a light weight model suitable for resource limited scenarios.

Savazzi[27], *et al.* proposed in the same year a new stochastic approach in which average path loss and target induced fluctuations of signal strength are jointly modelled by diffraction theory concept. The technique adopted a log-normal model for online prediction of target location. Performance of MLE and Bayesian MMSE methods such as geometric filter based and particle filter based were compared using RMSE. PF Bayesian tracking was found to be accurate among other methods. Combination of Bayesian localisation algorithm and particle filtering can be used for two-target monitoring with low complexity. In future it can be extended to multiple targets also.

Rampa[28], *et al.* proposed a physical model based on change in RSSI values for various non-cooperative human target positions between transmitter and receiver. A stochastic random variable formulated from RSSI values detected the target position analytically. Localisation accuracy was numerically evaluated using root mean square error for different values of target positions. Higher sensitivity was obtained near transmitter receiver positions. Large targets were better sensed than smaller ones. Highly apt deployment model for multi-link set ups.

Guo[29], *et al.* proposed a novel method for an accurate RSSI based localisation and tracking of the target especially in multipath scenarios, where chance of error is very high. The proposed exponential-Rayleigh (ER) method is an improvisation over existing RSSI method which consists of two parts. Rayleigh part was involved in finding out multi-path components induced by target. From this model excess path length was calculated. The efficiency of the method was experimentally proved using 95 per cent-percentile and mean by comparing with conventional magnitude models.

Caesar[30], *et al.* proposed an accurate algorithm suitable for resource restricted applications with low storage and computational requirements. Simple geometric features are used to represent shadowed links, probable target location and prior location. Usage of prior location estimate which remove outlier links, unreliable target locations, assigned appropriate RSSI based and distance based weights to approximate target locations. The method was found to be more robust to large errors out of which most of tracking errors are less than 1.1 m. The method highlights the importance of preceding information and link filter for a location approximation. Combination of received signal strength (RSS) and distance based weights gave best performance for GF algorithm. The algorithm performs better than BGA, radio tomographic imaging and sequential importance resampling. But the performance in cluttered outdoor environment was not that good as compared to indoor. The proposed algorithm can be used for multi-target tracking in future. Improvisation was made by researchers in link filtering[31].

Talampas[32], *et al.* extended their research in an enhanced multichannel GF algorithm that improves accuracy in cluttered environment. The algorithm used channel differences to impede the effects of multipath environment on the network's links. Minimum detected output based on each link's fade level and RSS variance improved detection of links at the intersection of targets. The method was found to be better along with RTI-FL

(Radio tomographic imaging-fade level) in a least multipath outdoor environment and best in cluttered indoor environment. The proposed method out performed existing RTI based multichannel methods by improved tracking accuracy and average execution time.

Savazzi[33], *et al.* proposed a novel, non-invasive and dynamic human sensing model supporting the real time localisation of an operator w.r.t robot movements using RSS value. The robot state act as jump linear Markovian system (JLMS) parameter for target tracking and interacting multiple model (IMM) filtering algorithm was adopted for state estimation of robot. Estimation error was found to be less than 0.2 m. A sensor fusion approach was also performed for DFL. IMM method using extended Kalman filtering for prediction of human activity in 2D, that outperformed time of flight (ToF), DFL Bayesian, fused ToF/DFL IMM, and fused ToF/DFL Bayesian channels. The DFL and sensor fusion algorithm effectively limited the impairments introduced by defective vision system.

3.1.1 Comparison of Techniques within Statistical Methods

The comparison of various models or techniques within different statistical methods are also explained in Table 2. Although statistical models are generally complex due to mathematical or stochastic configuration, geometrical model and Bayesian grid model are found to be less complex of all statistical models. Very few models were developed for multiple target tracking out of which exponential Rayleigh model was found to be a good statistical model for multi-target tracking.

3.2 Techniques-based on Compressive Sensing Methods

In compressive sensing based techniques, not all data is used for the analysis of the data. The available data is compressed and relevant data is only taken for proper acquision and reconstruction of original signal.

Yang[34], *et al.* proposes, a resource efficient and fast executing compressed maximum matching select (CMMS) algorithm in a real time scenario. A radio tomographic model is developed for mapping variations in RSS values in different links as a measure of target location in continuous space. The algorithm identifies the probable region and RSS values associated with only correlated links near that region for reconstructing the signal thus reducing the execution time. Tracking performance of a single and dual target was verified using proposed algorithm. After comparing with l1 minimisation algorithm, regularisation and Bayesian greedy matching pursuit (BGMP) algorithm, proposed algorithm was found to be fastest of all with average error less than 0.09m.

In the same year, Wang[35], *et al.* proposed an accurate differential RSS method that mitigate the effects of wrong identification of shadowed links. An outlier link filtering scheme improved the accuracy of the system. Maximum likelihood observation function incorporating particle filter scheme improved the robustness of the system. The proposed method was compared with differential RSS-without outlier detection, traditional RSS algorithms and was found to be robust. The PF algorithm was compared with compressive sensing, machine learning along with their respective differential RSS counterparts and mean tracking error was found to be significantly low to 0.99 m. Differential counter parts enhanced the performance much better than its conventional algorithms proving its universal nature. Multiple target detection is still an open question of research in this domain.

Ahmed[36], *et al.* proposed Ichnaea, an improved, robust, and low complex framework for DFL setup. The proposed system utilised a lightweight training period of two minutes for understanding the target free default environment. The motion detection module performance of proposed system was evaluated in three large scale realistic test beds deployed in WLAN cluttered environments using metrics like false positive, false negative, and F measure. Ichnaea excelled over other methods in terms of accuracy and robustness. Comparison of the model was also made with device free passive tracking systems like Nuzzer probabilistic system, quadratic discriminant analysis and linear discriminant analysis using median distance error and was found to be better.

Wang[37], *et al.* proposed multidimensional wireless-link-information (MDWL) using a recursive compressive sensing

Table 2. Statistical based DFL techniques comparison

Model/Algorithm	Parameter measured	Tracking Accuracy	Complexity	Computation overhead	Robust	Multipath Effect	Multi-target tracking
Geometric Filter Algorithm	RSS	Good	Low	Low	High	Moderate	-
Multi-channel geometric filter	RSS	Good	-	Low	Moderate	High	-
Jump Linear Markovian systems	RSS	Good	Moderate	-	Moderate	High	-
Lightweight Bayesian Grid Approach	RSS	Good	Low	Low	High	Low	-
Stochastic Bayesian Framework	Path loss, RSS	Good	Moderate	Low	-	Moderate	-
Ad-hoc diffraction model	RSS	Moderate	-	-	-	High	-
Exponential Rayleigh model	RSS	Good	-	-	-	High	Good
Probabilistic Cover Algorithm	RSS	Good	Low	-	-	High	-
Fade Level skew Laplace model	RSS	Good	Moderate	-	High	Moderate	Moderate
Spatial multipath based model	RSS	Good	Moderate	-	-	High	-

model for maximising performance. The link information was nurtured using sequential scanning of multi-frequency and multi-transmission power level in existing links. Tracking and cumulative probability of the proposed technique is compared with traditional DFL methods and was found to be very much better despite of increased scanning time requirement. To reduce the scanning time, orthogonal frequency division multiplexing was found to be a prospective method in future.

Wang[38]*, et al.* proposed a novel technique for DFL of multiple categorised target with less human effort. In the method localised models are generated from varying RSSI values across different categories as sensing vector space, preserving each value change based on geometric structure of the target. The so called transferring based CS algorithm for localisation should have prior knowledge of the target categories. Rigorous real time experiments conducted for checking the robustness and quality of the model was found to be effective.

3.2.1 *Comparison of Techniques within Compressive Sensing Methods*

The comparison of various models or techniques within different compressive sensing methods are also explained in Table 3. Out of the models that adopted compressive sensing method, Ichnaea and CMMS are found to be less complex and of low computational overhead. Moreover, CMMS model has considered multipath effect and despite of that multi-target tracking was also performed accurately. Thus the performance of CMMS model was found to be the best of all compressive sensing models.

3.3 Techniques-based on Radio Tomographic Imaging Methods

In radio tomographic imaging based DFL techniques, radio images are previously obtained at multiple positions of target. The exact position of the target can be assessed for the obtained radio image in real time environment. RTI models existing in two hybrid formats comprising compressive sensing and radio tomographic method as well as statistical and radio tomographic imaging are explained.

Wilson and Patwari[39], proposed behind the wall tracking of moving entities in a cluttered environment using variance based RTI technique with high accuracy. An image estimation of RSSI variance for different target affected links were developed from statistical models based on total power consumed in links and weighted function. The variance based RTI performed better through walls when compared to conventional RTI technique which failed to give reliable results. The average error was found to be less than two feet. Adequate improvements in mathematical models, physical layer design parameters, network protocols can enable the researcher to solve sparse recovery problem. Reliable tracking across dense walls is still an open research problem in this area.

Zhao and Patwari[40] analysed many variance based localisation and tracking methods of targets using radio frequency transceivers by deploying at required area of interest. In the conventional variance based RTI, intrinsic motion effect is averted. The main goal of the paper is to develop an image based on extrinsic motion and link measurements. In subspace decomposition method (SubVRT), various patterns are obtained in multi dimensions with improved noise rejection. In least square method (LSVRT), detection is made based on a Bayesian calculation by minimising a cost function. The performance of LSVRT was found to be better than other VRT estimators both in terms of accuracy, RMSE and mitigation of intrinsic motion noise. Kalman filter was applied to the estimators for tracking and found that VRTI is less robust compared to others.

Wang[41]*, et al.* designed a time and energy effective TOF based DFL through accelerating link scanning process and prior prediction of shadowed links with FDMA. The method exhibited improved location estimation from location information of wireless node and variation in distance measurement. Improved location accuracy was guaranteed by modelling DFL as sparse signal recovery problem by incorporating link information compress sensing framework. The technique incorporates link state estimation function using particle filter for prediction of shadowed links. Frequency division technique was employed for performing parallel scanning of shadowed links thereby decreased execution time. Energy consumption did not increase linearly with number of targets without any significant change in accuracy.

Wilson and Patwari[42], proposed a linear model for signal strength so as to develop an image of the attenuating object using radio tomographic imaging. The proposed elliptical weighted model with a noise factor is incorporated to develop a lower bound for the error so produced. The effect of number of nodes deployed and average error evaluated was found to be inversely related. The image recovery parameters are used for generating a smooth image. Future research in this domain is to find the best values of the image recovery parameters and to obtain real time representation of the DFL problem.

Seifeldin[43], *et al.* designed and developed an accurate, scalable, device free passive localisation technique called Nuzzer for single target detection in real time. The proposed method detects the target location based on a probabilistic based passive radio map generation. The discrete and continuous space estimator operation identified highest probable and

Table 3. Compressive sensing based DFL techniques comparison

Model/Algorithm	Parameter measured	Tracking accuracy	Complexity	Computation overhead	Robust	Multipath Effect	Multi-target tracking
Ichnaea	RSS	Good	Low	Low	High	Moderate	-
Multi- dimensional wireless link	RSS	Good	Low	Moderate	-	-	-
TLCS	RSS	Good	-	Moderate	High	-	Good
Differential RSS DFL	Differential RSS	Good	Low	Low	High	-	-
CMMS	RSS	Good	Low	Low	-	High	Moderate

accurate location of target respectively from RSSI vector. The performance of Nuzzer was compared with random and deterministic methods and was found to be highly promising and accurate. Line-of-sight problem was absent due to high penetrating ability of radio waves and its wide coverage. Future work can be extended in multiple target tracking, automatic radio map generation and optimisation of AP's location.

3.3.1 Comparison of Techniques within Radio Tomographic Imaging methods

The comparison of various models or techniques within different radio tomographic imaging methods are as explained in Table 4. In radio tomographic imaging models, multipath effect consideration is generally low because of its inability to assess external disturbances. Among the different models in the category, energy efficient time of flight method is the only method that attempted multi-targeting with reasonable accuracy. The complexity and computation cost were found to be low in this method at the expense of moderate single target tracking accuracy.

3.4 Techniques based on Machine Learning Methods

In machine learning methods, artificial intelligence is imparted to the system model for understanding the data and thereby predicting the parameter from that data. First the system will be trained with training set and analysed for a test set which is later verified by an experimental test bed.

Sigg[44], *et al.* proposed a device free activity identification based on RF variations in the channel for classification of environment and object localisation with at most accuracy. Classifying parameters used for device free activity recognition (DFAR) were time domain parameters. Activities are classified by k-NN classifier and their performances were found to be comparable based on accuracy and information score metrics. Better feature selections, coverage area, training excellences, multiple target activity recognition are the probable areas of future research.

Hong[45], *et al.* proposed, a device free based passive localisation array sensor (PLAS) for an efficient and robust DFL system to an indoor environment. The proposed PLAS system do not use RSS measurement but signal subspace features in wireless network. Design of statistical based outlier link abatement method removed unnecessary links and thus improving accuracy of model. Localisation accuracy improved in a single room set up. Centralised antennas were found to be highly accurate than distributed one with high dependence on PLAS accuracy. Localisation accuracy is less in two room set up. The proposed technique was compared against Nuzzer, K-NN (K- nearest neighbour), and random estimation and was found to be better. However, multiple object localisation using the technique is still under review.

Mager[46], *et al.* analysed degradation of localisation over time or changing environments and performed various test methods to mitigate it. A repeated experiment set up was arranged where 5 experiment sets were arranged with 4 different classifiers such as Random forest (RF), K-NN (K nearest neighbour), support vector machine (SVM), linear discriminant analysis (LDA). Performance of RF was found to be best as classifier parameter with error percent rate was found to be same for all technique. Simultaneous data processing from all channels was found to be better than individual processing but with increased complexity. Choice of best channel was obtained by correlation method. Channel selection using correlation method and classification using RF classifier may result in lower localisation error.

Wang[47] proposed DFL and activity recognition (DFLAR) in a wavelet framework that characterizes a shadowing effect map in time and frequency domain, thereby locating target with different activities. The highlight of the proposed model is its discriminatory nature and strength. The performance of wavelet based DFLAR was compared with time domain based DFLAR as well as time and frequency based DFLAR and was found to be better. Multi-target activity recognition is the challenging task in future.

3.4.1 Comparison of Techniques within Machine Learning methods

The comparison of various models or techniques within different machine learning methods are explained for understanding the efficiency and scope of each model in Table 5. In machine learning models, DFLAR with wavelet feature was found to be the one that attempted multiple target tracking by incorporating moderate multipath effect. The model is also simple when compared to the complexities of other machine learning models.

3.5 Comparison among DFL Categories

The scope of the DFL techniques by understanding the positive and negative traits of each category are also analysed in Table 6. Apart from choice of each category that depends on parameter requirement, the choice of suitable model from each of these different categories are equally important for improving the efficiency of proposed system in different applications.

Table 4. Radio tomographic imaging based DFL techniques comparison

Model/Algorithm	Parameter measured	Tracking accuracy	Complexity	Computation overhead	Robust	Multipath effect	Multi-target tracking
Energy efficient time of flight	TOF	Moderate	Low	Low	High	Moderate	Moderate
LVRTI	RSS	Good	-	-	High	Moderate	-
Nuzzer	RSS	Good	Moderate	-	Moderate	High	-
VRTI	RSS	Good	Moderate	Moderate	-	High	-
RTI	RSS	Good	Low	Low	-	Moderate	-

Table 5. Machine learning based DFL techniques comparison

Model/Algorithm	Parameter measured	Tracking accuracy	Complexity	Computation overhead	Robust	Multipath effect	Multi-target tracking
PLAS	RSS, Signal Eigen vector	Good	Moderate	Moderate	High	High	-
Fingerprint based DFL	RSS	Good	-	-	High	High	-
DFLAR with wavelet feature	Wavelet, RSS	Good	Low	-	High	Moderate	Good
DFAR	RSS	Good	Low	-	-	-	-

4. ANALYSIS AND FUTURE SCOPE

The various parameters taken under consideration for assessing the DFL models or techniques are tracking accuracy, complexity, computation overhead and so execution time, robustness[47], cluttered environment indoor or outdoor i.e. multipath effect consideration, single target tracking and multi target tracking etc. Almost all except two of the techniques are using RSS-based modality with desirable localisation accuracy. The techniques are so developed that they take minimum execution time and are robust to any environmental conditions. Most of them track the target with good accuracy and due consideration is given to multipath effect as most of the experimental test bed is indoor based.

In general, most of the techniques in the mentioned literatures followed RSS-based target localisation in device free environment due to its simplicity and promising nature. However, RSS is a highly sensitive signal parameter that changes abruptly based on environmental changes, supply source fluctuations, variations in gain of transceivers, finally affecting the performance of the localisation model. The techniques have adopted suitable changes in the model as well as in algorithm for improved efficiency of the system. Main parameters under consideration for improved efficiency and performance of the system were tracking and localisation accuracy which most of the models in the literatures are satisfying. Cluttered indoor environment and outdoor at times were considered in most of the models so as to incorporate the multipath effect in a changing environment thereby portraying the efficiency of the model. Some of the literatures have considered dynamically changing mobile target for understanding the system performance.

Consolidating the literatures, following are the scope for future research in DFL setup. Fluctuations in RSS due to physical phenomenon like temperature, humidity is difficult to analyse. Development of a model that understands the fluctuation of RSS due to target environment and physical environment is still an open areas of research. Most of the literatures are based on designing a model or algorithm for single target tracking and localisation. So there is a wide scope for research exploration in multi target tracking. Moreover, the designed DFL technique should achieve a promising efficiency through a simple, low complex, and robust system. Thus incorporating a low complex, low overhead design in DFL technique is also important. For analysing the effectiveness of a DFL model, the key parameters to be identified and analysed are tracking accuracy, complexity, computation overhead and so execution time, robustness. RSS changes in measurement is also depending upon physical nature of the target such as size, shape as well as distance between target and nodes. For instance, signal strength varies similarly with a small target close to transceiver as well as a large target far from transceiver. Thus, proper understanding of physical dimensions of the target is also necessary for accurate localisation. Depending upon the position of the target the RSSI fluctuations are also occurring. This RSSI values again changes with different degrees of complexity of room.

5. CONCLUSIONS

DFL in wireless sensor network is an upcoming area of research with profound chance of exploration. The evolution of DFL is analysed by sequential differencing between

Table 6. DFL methods: A comparison

Categories	Positive traits	Negative traits
Statistical	Robustness. No need of offline calibration.	No prior information is available. Computational complexity. External parameters are not considered in modelling.
Machine learning	Acceptable accuracy. Designable in dangerous and unreachable applications. Applicable to changing environments. Low complex estimation to mathematical models.	Large historical data requirement. Maintenance difficulty. Time consuming. Identification of relevant parameters for online phase.
Compressive sensing	Sparse information utilised for signal reconstruction. Limited number of active sensors. Limited storage and computational power.	Changing environment affects accuracy. Computationally expensive. Lack of robustness.
Radio tomographic imaging	Wide coverage. Acceptable performance.	Challenging radio map building. Tedious calibration procedure. Negative impact of outlier links not considered. Lack of theoretical evaluation and proofs. Requirement of large number of sensor nodes.

device based localisation and DFL with their categories. The importance of DFL is highlighted through various application scenarios. The scope of reviewed DFL techniques and the modalities for attaining the position of target is assessed by the researcher by venturing into the latest related literatures. The DFL techniques so surveyed is classified into four broad categories as statistical, machine learning, compressive sensing and radio tomographic imaging. Performance of the DFL models are assessed based on qualitative parameters like accuracy, complexity, computation requirements, multipath considerations, number of targets tracked, robustness etc. Gaps found in each literature is summarised for orienting the research further in appropriate directions.

REFERENCES

1. Enge, P. & Misra, P. Special issue on global positioning system. *In* Proceedings of the IEEE, 1999, **87**(1), 3-15. doi: 10.1109/jproc.1999.736338.
2. Youssef, M.; Mah, M. & Agrawala, A. Challenges: device-free passive localization for wireless environments. *In* Proceedings of the 13th annual ACM international conference on Mobile computing and networking - MobiCom 07, 2007, pp. 222–229. doi: 10.1145/1287853.1287880.
3. Bahl, P. & Padmanabhan, V. RADAR: An in-building RF-based user location and tracking system. *In* Proceedings IEEE INFOCOM 2000. Conference on Computer Communications. Nineteenth Annual Joint Conference of the IEEE Computer and Communications Societies (Cat. No.00CH37064), 2000. doi: 10.1109/infcom.2000.832252
4. Want, R.; Hopper, A.; Falcao, V. & Gibbons, J. The active badge location system. *ACM Transactions on Information Systems*, 1992, **10**(1), 91-102. doi: 10.1145/128756.128759
5. Priyantha, N. B.; Chakraborty A. & Balakrishnan, H. The cricket location-support system. *In* Proceedings of the 6th Annual International Conference on Mobile Computing and Networking - MobiCom 00, 2000. doi: 10.1145/345910.345917
6. Ramesh, M. V. Design, development, and deployment of a wireless sensor network for detection of landslides. *Ad Hoc Networks*, 2014, **13**, 2-18. doi: 10.1016/j.adhoc.2012.09.002.
7. Barsocchi, P.;Potortì, F. & Nepa, P. Device-free indoor localization for AAL applications. *In* Lecture Notes of the Institute for Computer Sciences, Social Informatics and Telecommunications Engineering Wireless Mobile Communication and Healthcare, 2013, pp.361-368. doi: 10.1007/978-3-642-37893-5_40.
8. Shukri, S.;Kamarudin, L. M.; Ndzi, D. L.;Zakaria, A.; Azemi S. N.; Kamarudin K. & Zakaria, S. M. RSSI-based device free localization for elderly care application. *In* Proceedings of the 2nd International Conference on Internet of Things, Big Data and Security, 2017. doi: 10.5220/0006361901250135.
9. Wang, Y.; Wu, K. & Ni, L. M.WiFall: Device-free fall detection by wireless networks. *IEEE Transactions on Mobile Computing*, 2017, **16**(2), 581-594. doi: 10.1109/tmc.2016.2557792
10. Liu X.; Cao, J.; Tang, S.; Wen, J. & Guo, P. Contactless respiration monitoring via off-the-shelf WiFi devices. *IEEE Trans. Mobile Comput.*, 2016, **15**(10), 2466-2479. doi: 10.1109/tmc.2015.2504935.
11. Wang, H.; Zhang, D.; Wang, Y.; Ma, J.; Wang, Y. & Li, S. RT-Fall: A real-time and contactless fall detection system with commodity WiFi Devices. *IEEE Trans. Mobile Comput.*, 2017, **16**(2), 511-526. doi: 10.1109/tmc.2016.2557795.
12. Patwari, N. & Wilson, J. RF Sensor networks for device-free localization: Measurements, models, and algorithms. *In* Proceedings of the *IEEE*, 2010, **98**(11), 1961-1973. doi: 10.1109/jproc.2010.2052010.
13. Deak, G.; Curran, K. & Condell, J. A survey of active and passive indoor localization systems. *Comput. Commun.*, 2012, **35**(16), 1939-1954. doi: 10.1016/j.comcom.2012.06.004.
14. Pirzada, N.; Nayan, M. Y.; Subhan, F.; Hassan, M. F. & Khan, M. A. Comparative analysis of active and passive indoor localization systems. *AASRI Procedia*, 2013, **5**, 92-97. doi: 10.1016/j.aasri.2013.10.063.
15. Pirzada, N.; Nayan, M. Y.; Hassan, F. S. & Khan, M. A. Device-free localization technique for indoor detection and tracking of human body: A survey. *Procedia - Social and Behavioral Sciences*, 2014, **129**, 422-429. doi: 10.1016/j.sbspro.2014.03.696.
16. Kivimaki, T.;Vuorela, T.;Peltola, P. & Vanhala, J. A review on device-free passive indoor positioning methods. *Int. J. Smart Home*, 2014, **8**(1), 71-94. doi: 10.14257/ijsh.2014.8.1.09.
17. Xiao, J.; Zhou, Z.; Yi, Y. & Ni, L.M. A survey on wireless indoor localization from the device perspective. *ACM Comput. Surveys*, 2016, **49**(2), 1-31. doi: 10.1145/2933232.
18. Seifeldin, M. & Youssef, M. A deterministic large-scale device-free passive localization system for wireless environments. *In* Proceedings of the 3rd International Conference on PErvasive Technologies Related to Assistive Environments - PETRA 10, 2010. doi: 10.1145/1839294.1839355.
19. Palipana, S.;Pietropaoli, B. & Pesch, D. Recent advances in RF-based passive device-free localization for indoor applications. *Ad Hoc Networks*, 2017, **64**, 80-98. doi: 10.1016/j.adhoc.2017.06.007.
20. Deak, G.; Curran, K. & Condell, J. Evaluation of smoothing algorithms for a rssi-based device-free passive localization. *In* Advances in Intelligent and Soft Computing Image Processing and Communications Challenge, 2010, **2**, 469-476. doi: 10.1007/978-3-642-16295-4_52.
21. Fink, A.; Lange, J. & Beikirch, H. Human body detection using redundant radio signal strength readings for reliable device-free localization. *Ambient Assisted Living: Advanced Technologies and Societal Change,* 2015, 127-

137.
doi: 10.1007/978-3-319-11866-6_10.

22. Patwari, N. & Wilson, J. Spatial models for human motion-induced signal strength variance on static links. *IEEE Trans. Info. Forensics and Security*, 2011, **6**(3), 791-802.
doi: 10.1109/tifs.2011.2146774.
23. Wilson, J. & Patwari, N. A fade-level skew-laplace signal strength model for device-free localization with wireless networks. *IEEE Trans. Mobile Comput.*, 2012, **11**(6), 947-958.
doi: 10.1109/tmc.2011.102.
24. Chen, J.; Li, J. & Lai, T. H. Trapping mobile targets in wireless sensor networks: An energy-efficient perspective. *IEEE Trans. Vehicular Technol.*, 2013, **62**(7), 3287-3300.
doi: 10.1109/tvt.2013.2254732.
25. Zhang, D.; Lu, K.; Mao, R.; Feng, Y.; Liu, Y.; Ming, Z. & Ni, L. M. Fine-grained localization for multiple transceiver-free objects by using RF-based technologies. *IEEE Trans. Parallel Distributed Sys.*, 2014, **25**(6), 1464-1475.
doi: 10.1109/tpds.2013.243.
26. Wang, J.; Gao, Q.; Cheng, P.; Yu, Y.; Xin, K. & Wang, H. Lightweight robust device-free localization in wireless networks. *IEEE Trans. Indust. Electron.,* 2014, **61**(10), 5681-5689.
doi: 10.1109/tie.2014.2301714.
27. Savazzi, S.; Nicoli, M.; Carminati, F. & Riva, M. A Bayesian approach to device-free localization: modeling and experimental assessment. *IEEE J. Selected Topics Signal Proces.*, 2014, **8**(1), 16-29.
doi: 10.1109/jstsp.2013.2286772.
28. Rampa, V.; Savazzi, S.;Nicoli, M. & Damico, M. Physical modeling and performance bounds for device-free localization systems. *IEEE Signal Proces. Lett.*, 2015, **22**(11), 1864-1868.
doi: 10.1109/lsp.2015.2438176.
29. Guo, Y.; Huang, K.; Jiang, N.; Guo, X.; Li, Y. & Wang, G. An exponential-rayleigh model for rss-based device-free localization and tracking. *IEEE Trans. Mobile Comput.*, 2015, **14**(3), 484-494.
doi: 10.1109/tmc.2014.2329007.
30. Talampas, M. C. & Low, K. A Geometric filter algorithm for robust device-free localization in wireless networks. *IEEE Trans. Indust. Info.*, 2016, **12**(5), 1670-1678.
doi: 10.1109/tii.2015.2433211.
31. Sreeraj, S. J. & Ramanathan, R. Improved geometric filter algorithm for device free localization. *In* 2017 International Conference on Wireless Communications, Signal Processing and Networking (WiSPNET), 2017, pp. 940-944
doi: 10.1109/wispnet.2017.8299895.
32. Talampas, M. C. & Low, K. An enhanced geometric filter algorithm with channel diversity for device-free localization. *IEEE Trans. Instrument. Measur.*, 2016, **65**(2), 378-387.
doi: 10.1109/tim.2015.2490818.
33. Savazzi, S.; Rampa, V.; Vicentini, F. & Giussani, M. Device-free human sensing and localization in collaborative human–robot workspaces: A case study. *IEEE Sensors J.*, 2016, **16**(5), 1253-1264.
doi: 10.1109/jsen.2015.2500121.
34. Yang, Z.; Huang,K.;Guo, X. & Wang, G. A real-time device-free localization system using correlated RSS measurements. *EURASIP J. Wireless Commun. Networking*, 2013, **2013**(1).
doi: 10.1186/1687-1499-2013-186.
35. Wang, J.; Gao, Q.; Yu, Y.; Cheng, P.; Wu, L. & Wang, H. Robust device-free wireless localization based on differential RSS measurements. *IEEE Trans. Indust. Electron.*, 2013, **60**(12), 5943-5952.
doi: 10.1109/tie.2012.2228145.
36. Saeed, A.;Kosba, A. E. & Youssef, M. Ichnaea: A low-overhead robust WLAN device-free passive localization system. *IEEE J. Selected Topics Signal Proces.*, 2014, **8**(1), 5-15.
doi: 10.1109/jstsp.2013.2287480.
37. Wang, J.; Gao, Q.; Wang, H.; Cheng, P. & Xin, K. Device-free localization with multidimensional wireless link information. *IEEE Trans. Vehicular Technol.*, 2015, **64**(1), 356-366.
doi: 10.1109/tvt.2014.2318084.
38. Wang, J.; Chen, X.; Fang, D; Wu, C. Q.; Yang, Z. & Xing, T. Transferring compressive-sensing-based device-free localization across target diversity. *IEEE Trans. Indust. Electron.*, 2015, **62**(4), 2397-2409.
doi: 10.1109/tie.2014.2360140.
39. Wilson, J. & Patwari, N. See-through walls: Motion tracking using variance-based radio tomography networks. *IEEE Trans. Mobile Comput.*, 2011, **10**(5), 612-621.
doi: 10.1109/tmc.2010.175.
40. Zhao, Y. & Patwari, N. Robust estimators for variance-based device-free localization and tracking. *IEEE Trans. Mobile Comput.*, 2015, **14**(10), 2116-2129.
doi: 10.1109/tmc.2014.2385710.
41. Wang, J.; Gao, Q.; Yu, Y.; Zhang, X. & Feng, X. Time and energy efficient TOF-based device-free wireless localization. *IEEE Trans. Indust. Info.*, 2015, 1-1.
doi: 10.1109/tii.2015.2501225.
42. Wilson, J. & Patwari, N. Radio tomographic imaging with wireless networks. *IEEE Trans. Mobile Comput.,* 2010, **9**(5), 621-632.
doi: 10.1109/tmc.2009.174.
43. Seifeldin, M.; Saeed, A; Kosba, A. E.; El-Keyi, A. & Youssef, M. Nuzzer: A large-scale device-free passive localization system for wireless environments. *IEEE Trans. Mobile Comput.,* 2013, **12**(7), 1321-1334.
doi: 10.1109/tmc.2012.106.
44. Sigg, S.; Scholz, M.; Shi, S.; Ji, Y. & Beigl, M. RF-sensing of activities from non-cooperative subjects in device-free recognition systems using ambient and local signals. *IEEE Trans. Mobile Comput.*, 2014, **13**(4), 907-920.
doi: 10.1109/tmc.2013.28.
45. Hong, J. & Ohtsuki, T. Signal eigenvector-based device-free passive localization using array sensor. *IEEE Trans. Vehicular Technol.*, 2015, **64**(4), 1354-1363.
doi: 10.1109/tvt.2015.2397436.

46. Mager, B.;Lundrigan, P. & Patwari, N. Fingerprint-based device-free localization performance in changing environments. *IEEE J. Selected Areas Commun.*, 2015, **33**(11), 2429-2438.
doi: 10.1109/jsac.2015.2430515.
47. Wang, J.; Zhang, X.; Gao, Q.; Ma, X.; Feng, X. & Wang, H. Device-free simultaneous wireless localization and activity recognition with wavelet feature. *IEEE Trans. Vehicular Technol.*, 2017, **66**(2), 1659-1669.
doi: 10.1109/tvt.2016.2555986.

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