Degree based WCL for Video Endoscopic Capsule Localization

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***Abstract*— Wireless video capsule endoscope (VCE) is used to diagnose lesions along digestive tracts. For proper diagnosis, it is necessary to know the exact location of the lesions which may be estimated by localizing the VCE. In this paper, we propose a simple VCE localization approach using static and dynamic degree based weighted centroid localization (WCL). In our proposed approach, a sensor array of eight receivers is used to estimate the distance of the moving capsule. The estimated distance is then raised to a higher degree to reduce the weight of the remote sensors marginally lower. We propose a sub-optimal method of both static and dynamic degree calculation using the estimated distances. We also analytically compute the optimal values of the degree to set benchmark to compare the performance of our proposed sub-optimal methods. We develop a $3D$ simulation platform using MATLAB to show the results and to verify the accuracy. We use indices named localization error (LE), average localization error (ALE), standard deviation (STD) and the normalized error to evaluate the performance. Using static optimal degree, the ALE is 5.19 mm where ALE of 6.55 mm is reachable using the sub-optimal method. For dynamic degree, ALE using optimal degree is 3.8 mm, while the ALE using sub-optimal degree is 6.27 mm. Thus, our proposed algorithms approach benchmark accuracy even if we change the dimension of the sensor network. The performance is also compared to the existing algorithms in the literature which shows better performance using our proposed algorithms.**

I. Introduction

Video capsule endoscope (VCE) is used to send clear images of abnormalities of the gastrointestinal (GI) tract. Localization of the VCE is the process of determining its unknown location while it travels through the GI tract. There are very few algorithms available in the literature which proposes system to localize the VCE. Some of those are based on electromagnetic field strength and some on magnetic field strength. Magnetic field strength based localization system require extra space of the capsule. Our focus is to develop an easy and cost effective VCE localization system based on radio frequency (RF).

RF localization algorithms may be range-based [1] or range-free [2]. In range-based schemes, nodes determine their location based on distance or angle estimates to some reference points. Such estimates may be acquired through different methods, such as time of arrival (TOA) [3], time difference of arrival (TDOA) [4], angle of arrival (AOA) [5], or received signal strength indicator (RSSI) [6]. The most common range-based algorithm is trilateration. Trilateration is a simple positioning technique [7], which estimates the mobile nodes location by intersection of the circles, each centered on the anchor node position, with a radius equals to the estimated distance between the mobile node and the anchor node. Triangulation [8] is usually employed to convert the proximity data into position information using the properties of triangles to calculate distances. In [9], the authors propose a lightweight range-free localization scheme using mobile anchor nodes equipped with GPS which broadcasts its coordinates to the sensor nodes as it moves through the network. Range-free algorithms are popular due to its simplicity and robustness to changes in wireless propagation properties. Centroid localization (CL) [2] is a range-free RF-based localization method in which the receiver localizes itself to the centroid of a set of proximate reference points using a connectivity metric. In CL, all points are assumed to be equally near the target node. Weighted centroid localization (WCL) [10] aims to improve localization accuracy by introducing greater weight to some points which are more close than others and less weight to the farther points. In the literature, there are several analysis to improve the accuracy of WCL. Most of those are for indoor applications. In [11]- [12], the algorithms are based on RSSI which take the reciprocal of the sum and the sum of the reciprocals of distances to calculate the weight. The authors in [13] considered the sum of the reciprocal of the distances and the side length of the triangle to calculate the weight. The average localization error reported in [10] is 7.42 m, in [11] is 10.14 m, in [12] is 2.54 m and in [13], it is 2.33 m. In [14], the authors used the node degree based WCL and in [15], the authors proposed linear-regression-based WCL to improve the performance of hop count localization using centralization and calibration using linear regression and correction. The mean localization error using [14]- [15] is close to 1.38 m. In [16], the authors replace the weight with the sum of the distance reciprocals and use the correction factor as the degree of distance. The average error reported is 0.5125 m. In [17], the authors raises the distance to different degree and for a specific degree they proposes a position refinement by finding offline calibration parameters. They have reported 0.13 m mean error using 6.25×10^{-3} m resolution. In [18], the authors introduces dynamic weighting factors that are solely dependent on the correlation of the RSSI and reports mean error of 5.3% or 0.053 m. For very short range, the authors in [19] propose a real-time RSSI-based tracking system using an advanced calibration method and filtering techniques in close-proximity of up to 1 m. Their experiment shows distance estimation error of 0.7 cm with standard deviation of 4 cm for a single measurement. However, the correction range algorithms in [15]- [19] requires the prior knowledge of the original distance to find the correction coefficient. In [20], the authors used weight-compensated WCL algorithm based on RSSI (WCWCL-RSSI) to estimate the position without any knowledge of the path loss exponent and other prior information. The maximum average error reported is $2.81\ m$.

There are very few algorithms proposed in the literature to localize the video endoscopic capsule. Most of the proposed algorithms are range-based. In [21], [22], the authors work on channel modeling for medical implant communication services (MICS). In [21], the authors model the electromagnetic (EM) propagation considering the absorption characterization in GI parts of human body and its impact on propagation model. The simulation results are in good agreement with the finite-difference-time-domain (FDTD) measurements. In [22], authors construct an immersive visualization environment to characterize RF propagation from medical implants and to model the statistical path loss for MICS channels. The model is based on four near surface and two deep tissue implant applications in a typical male human body. In [23], a review on VCE localization literature is presented. In [24], the paper presents a capsule endoscope localization system which utilizes only RSSI to estimate the location using maximum likelihood (ML) estimation and least squares (LS) method. The simulation results show that the ML localization improves the performance by 80 percent, as compared with the LS localization. In [25], the linear least square estimation is used to estimate the initial position of the source based of phase difference of arrival followed by a non-linear least square method to improve the localization accuracy. The reported position estimation error is within $1\ cm$ in $2D$ case for homogeneous and heterogeneous phantom. It is extended to $3D$ case for homogeneous cylinder case giving error within $1\ cm$. In [26], the authors proposes an algorithm using RFID of the antennas to $3D$ coordinates of capsule using center of gravity location estimation algorithm. The mean estimation error is $2\ cm$ as reported. In [27], the authors discuss system and method of determining the real-time location of an omni-directional RF system while the target transmitter is moving freely inside an inaccessible organ using triangulation algorithm. They have modelled the RF system and simulate the effects of organs on signal quality at various distances. The average error is 25% as reported. Most of the reported methods [24]–[27] requires TOA or RSS estimation. However, some unique challenges exist for in-body localization due to the complex nature within the human body. In [28], the authors directly estimate the location of the capsule (as the emitter) without going through the intermediate stage of TOA or signal strength estimation. They have reported $1.5-2\ cm$ average error using $8-16$ sensors. In [29], the authors investigate the potential accuracy limit for RSS triangulation based capsule localization in the human GI tract and reports average localization error of $48\ mm$ using 32 sensors. In [30], the authors propose a RSSI based video capsule endoscope (VCE) localization approach where a wearable antenna array of eight sensors is used to localize the capsule using adaptively linearized linear least square -WCL algorithm. They propose signal path loss linearization using the extracted signal parameters considering minimum path loss deviation. Then, the distance-dependent linearized path loss is used to calculate the weight and the position using WCL. Hence they go through a calibration process using the initial estimated positions which needs prior knowledge of the real positions of target which is practically impossible. The authors report mean square error (MSE) of $138.6\ mm$ with standard deviation $61.14\ mm$ before calibration and MSE of $5.15\ mm$ with STD $3.5\ mm$ after applying calibration, respectively using $600mm \times 600mm \times 600\ mm$ dimension of the sensor network of 8 sensors.

Most of the reported VCE localization algorithms [24]–[29] are based on trilateration or triangulation approach which can compute location using distance and angle information of triangle formed by three reference sensor nodes [31]. However, for more number of sensor nodes, it's computational complexity increases. The performance of the trilateration or triangulation based methods in [24]–[29] also require very precise knowledge on channel parameters, because its performance decreases excessively with estimation errors in channel [31]. As human body is a complex environment of experimentation, a simple localization approach with less computational complexity is required. WCL [10] is a simple localization approach [20] which can estimate location using three or more sensors with less computational complexity, less hardware cost and less communication overhead [20], [32]. It has attracted a lot of interests [12]–[20] in outdoor environment because of simplicity and robustness to changes in wireless propagation properties. Though it is dependent on beacon numbers and placements, the accuracy can be significantly improved using more sensors [31]. As human body is extremely heterogeneous media, the channel suffers severe multipath propagation and heavy shadow fading due to organs of different electrical parameters [22], [24]. WCL is much more robust against errors in the estimated channel model parameters [20], [31]. Thus, for a complex environment as human body, WCL is an appropriate choice for VCE localization.

In this paper, we propose two algorithms of video endoscopic capsule localization using static and dynamic degree based WCL. We propose a sub-optimal method of degree calculation for static and dynamic cases. As the received signal is scattered due to the random shadowing and multipath propagation effects of non-homogeneous environment, we linearize the path loss considering minimum path loss deviations. The distance is then calculated using the linearized path loss. The calculated distance is raised to a higher degree to decrease the weight of the higher distance sensors rationally and to calculate the weight. The static sub-optimal degree is calculated using the maximum distance covered by the sensors and the dynamic sub-optimal degree is calculated using the difference of estimated distance to a reference distance. We also analytically compute the optimal values for the static and dynamic degrees and set the values as the benchmark accuracy. We develop a simulation tool using MATLAB to verify the accuracy of our proposed static and dynamic degree based algorithms using different dimension of the sensor network. We observe that using our proposed optimal static degree, an average localization error (ALE) of $5.19\ mm$ with standard deviation (STD) of $4.18\ mm$ is reachable, where using the suboptimal static degree, we can achieve ALE of $6.55\ mm$ with STD of $6.61\ mm$. Again, using the dynamic degree, the optimal WCL accuracy improves significantly with ALE of $3.8\ mm$ and STD of $3.14\ mm$. Using sub-optimal dynamic

TABLE I

NOTATIONS

M	No. of total positions of the target (1-2530 for our simulation system)
N	No. of sensors used to localize the capsule which is 8 in our proposed algorithm
Tx	Transmitter
Rx	Receiver
P_T	Capsule transmitted power in dB
$RSSI$	Matrix ($N \times M$) containing the received signal in dB
$RSSI_{i,m}$	Received signal strength at i^{th} sensor from m^{th} position of the target
$d_{i,m}$	Distance of the i-th sensor and target for m^{th} position of the target
d_{max}	Maximum distance of the target and sensor
d_{min}	Minimum distance of the target and sensor
$S_{PL}(d_0)$	Path loss at reference distance d_0 of the target which is less than $d_{i,m}$
$S_D(0, \sigma_{RSS}^2)$	Random variable with zero mean and standard deviation σ_{RSS}
α	Path loss exponent
σ_{RSS}	Standard deviation of the random variable
$S_{PL}(d_{i,m})_{lin}$	Mean or linearized path loss of i-th sensor for m-th position of the target
$W_{i,m}$	Weight of the i-th sensor for m-th position of the target
$W_{(i,m)_{sopt}}$	Weight using Static optimal degree
$W_{(i,m)_{ssopt}}$	Weight using Static sub-optimal degree
$W_{(i,m)_{dopt}}$	Weight using Dynamic optima degree
$W_{(i,m)_{dsopt}}$	Weight using Dynamic sub-optimal degree
g	Degree of distance
g_{sopt}	Static optimal degree
g_{ssopt}	Static sub-optimal degree
g_{dopt}	Dynamic optimal degree
g_{dsopt}	Dynamic sub-optimal degree
B_i	The i-th sensor's position
x_i	i-th sensor's x-coordinate
y_i	i-th sensor's y-coordinate
z_i	i-th sensor's z-coordinate
R	M Real positions of the target in vector form
R_m	m-th real position of the target
E	M Estimated positions (using traditional WCL) of the target in vector form
E_m	Estimated position for m-th location of target using traditional WCL
P_m	Estimated position for m-th location of target using proposed WCL
P_{m_s}	Estimated position of the m-th position of target using static degree based WCL
P_{m_d}	Estimated position of the m-th position of target using dynamic degree based WCL
P_s	M Estimated positions of the target using static degree based WCL in vector form
P_d	M Estimated positions of the target using dynamic degree based WCL in vector form
x_e	x-coordinate of estimated position
x_r	x-coordinate of real position
y_e	y-coordinate of estimated position
y_r	y-coordinate of real position
z_e	z-coordinate of estimated position
z_r	z-coordinate of real position
LE_m	Localization error for m-th position of target
ALE	Average localization error
STD	Standard deviation of localization error

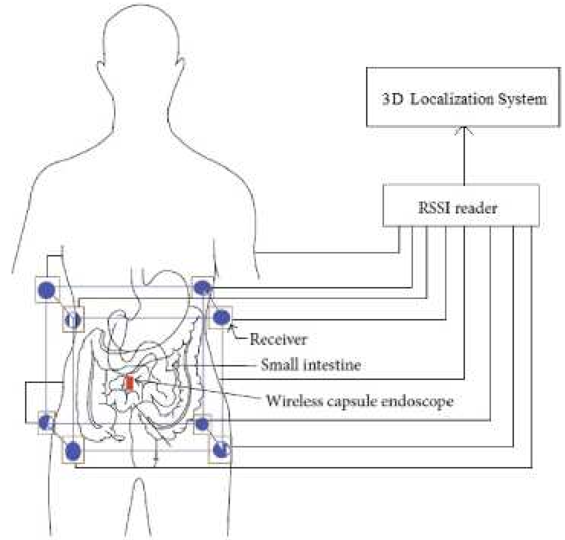

Fig. 1. Video Capsule Endoscope (VCE) localization approach.

degree, ALE of 6.27 mm with STD of 5.96 mm is possible to reach. It is also observed that our proposed algorithms perform equally well with changes in sensor network dimension.

II. SYSTEM OVERVIEW

We use the system set-up as shown in Fig. 1 to find the location of the capsule using our proposed static and dynamic degree based WCL algorithm. The system consists of a capsule, eight receiver sensors, RSSI reader, and a localization system. The capsule transmits RF signal while traveling through the small intestine. We consider the dimension of the small intestine as $240mm \times 280mm \times 360mm$. A body surrounded wearable antenna array of eight RF receivers are used to receive the signal of the moving capsule for localization. Hence, we consider the distance of the target from the sensors to calculate weight of the sensors position. As RSSI is attenuated with varying distance of transmitter and receiver due to the medium of propagation, we consider RSSI as a measure of Tx-Rx separation. The sensors measure the RSSI of the received signal and sent it to the central localization system. The localization system process the RSSI and the known coordinate sets of the sensors to calculate the three-dimensional ($3D$) positions of the capsule using the proposed WCL based localization algorithm. WCL is a localization algorithm which finds the average coordinate point giving greater weights to closer points and lower weights to farther points.

Figure 2 shows the architecture of the proposed system which consists of a RF transmitter equipped in the capsule, eight RF receiver modules (sensors), RSSI reader (microcontroller), and the localization tool. The sensors are configured as RF receivers which receive the signal transmitted from the moving capsule transmitter and measures the received signal strength indicator (RSSI). The transmitter transmits radio signal using isotropic antenna radiating the same intensity of

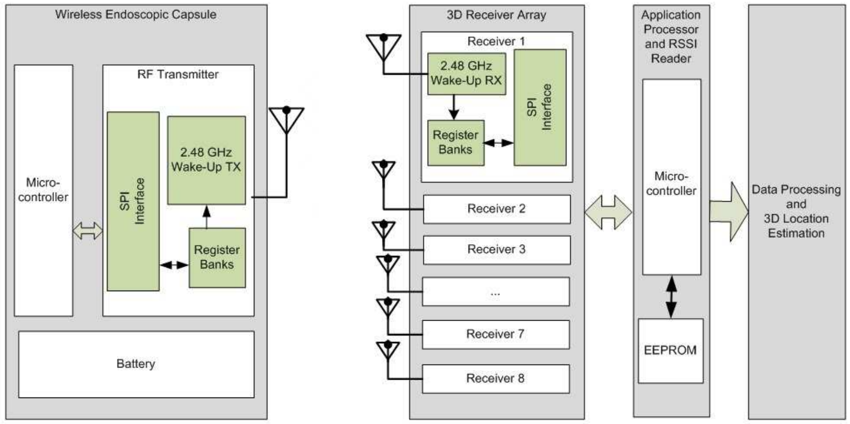

Fig. 2. Architecture for the proposed localization approach.

radio waves in all directions periodically. Micro-controller unit (MCU) is used to configure the transceiver modules (Tx or Rx) and to read-write data. MCU is used as the RSSI reader which reads the measured RSSI from the Rx and send it to the CPU. Finally the localization tool calculates the Tx-Rx separation distance (d_i) from the corresponding RSSI and then estimates the location using the proposed static and dynamic degree based WCL algorithms. The localization tool is developed using MATLAB. Most of the notations and symbols used in the whole paper are listed in Table I.

III. Channel modelling for In-body Localization

A channel model is required in determining the propagation characteristics in a particular environment. By analyzing the signal propagation from Tx to Rx for a number of experimental locations, a channel model is developed. The propagation characteristics depend upon the distance between the two antennas, the medium and the environment (buildings and other objects) of propagation. In this paper, the Tx-Rx separation distance is used to localize the capsule. The received power $P_R(d)$ and the path loss $P_L(d)$ is related to the distance d through Friis equation [33] as

$$\text{Received Power, } P_R(d) = \frac{P_T G_t G_r \lambda^2}{4\pi^2 d^2 L} \tag{1}$$

$$\text{and Path loss, } P_L(d) = \frac{4\pi^2 d^2 L}{\lambda^2}, \tag{2}$$

where, P_T is the transmitted power, G_t is the transmitter antenna gain, G_r is the received power gain, L is the system loss factor not related to propagation ($L \geq 1$), and λ is the wavelength of the transmitted signal. The path loss is the loss of signal strength while it propagates through the medium. Mathematically, it can be explained as the difference (in dB) between the transmitted signal power and the received signal power as

$$\text{Path Loss = Transmitted power - Received Power.} \tag{3}$$

The lognormal shadowing model [34] can be used to model the path loss statistically at location d as a random and log-

TABLE II
THE PARAMETERS OF IMPLANT TO BODY SURFACE PATH LOSS MODEL [22]

Implant to body surface	$S_{PL}(d_0)$	α	σ_{RSS}
Deep-Tissue	47.14	4.26	7.85
Near Surface	49.81	4.22	6.81

normally distributed random variable as follows

$$S_{PL}(d) = S_{PL}(d_0) + 10\alpha \log_{10}\left(\frac{d}{d_0}\right) + S_D(0, \sigma^2_{RSS}), \tag{4}$$

where, d_0 is the reference distance and $d \geq d_0$. Path loss exponent, α heavily depends on the environment through which RF signal is propagating. For free space, value of α is equal to 2. For human body, much higher value for the path loss exponent is expected. $S_D(0, \sigma^2_{RSS})$ is the random deviation of the path loss around the mean with standard deviation σ_{RSS} in dB caused by different materials and antenna gain in different directions. The signal propagated through the human body is deviated due to the shadowing effect of the non-homogeneous medium. We use the above lognormal shadowing model to model the signal propagation path loss between the sensor and the target VCE inside the human body. For a particular location of the VCE, we can calculate the path loss from the measured received power of the sensors using Eq. 3. Then we can calculate distance by replacing the path loss in Eq. 4 if the signal parameters are known. The statistical path loss model for medical implant communication was developed by the national institute of science and technology (NIST) at the MICS band [22]. The parameters of implant to body surface path loss model are summarized in Table II. The resolution of their simulation system is 2 mm. Deep tissue implant scenario considers endoscopy capsule applications for upper stomach (95 mm below body surface) and lower stomach (118 mm below body surface). Using Eq. 4, we can represent the signal propagation path loss of m received signals for m possible

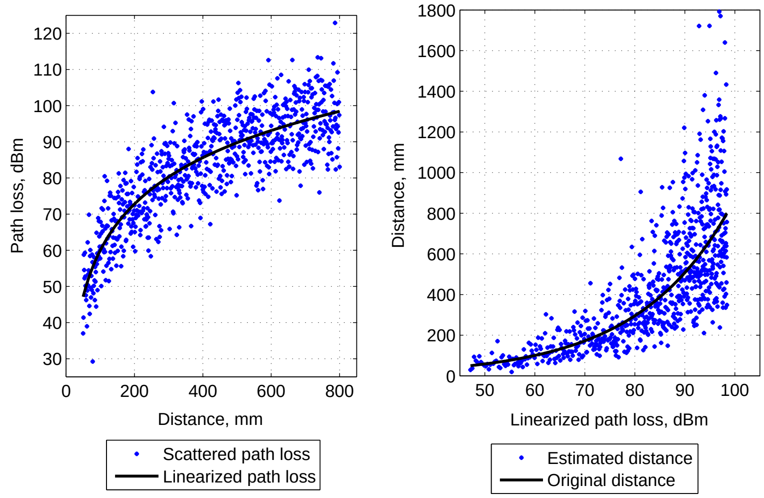

Fig. 3. (a) Statistical path-loss model (deep-tissue implant scenario); (b) Estimated and real distances.

positions of the capsule in matrix form as

$$\begin{pmatrix} S_{PL}(d_1) \\ S_{PL}(d_2) \\ \vdots \\ S_{PL}(d_m) \end{pmatrix} = \begin{pmatrix} 1 & 10\log_{10}(d_1/d_0) & 1 \\ 1 & 10\log_{10}(d_2/d_0) & 1 \\ \vdots & \vdots & \vdots \\ 1 & 10\log_{10}(d_m/d_0) & 1 \end{pmatrix} \begin{pmatrix} S_{PL}(d_0) \\ \alpha \\ S_D(0,\sigma^2_{RSS}) \end{pmatrix}. \quad (5)$$

Using the path loss attenuation exponents $(S_{PL}(d_0),\ \alpha$ and $\sigma_{RSS})$ of Table II, we model the path loss for deep-tissue implant scenario of human body for m possible positions of the capsule using Eq. 5. Figure 3(a) shows the scattered path loss for a range of Tx-Rx separation distance $50mm - 800mm$, where the path loss is scattered around a mean. It is due to the random deviations $S_D(0,\sigma^2_{RSS})$ which is caused by the non-homogeneous medium of propagation. Figure 3(b) shows the distance estimated using Eq. 4 from scattered path loss. The distance cannot be calculated accurately using scattered path loss which in turn increases the localization error. As we can see from Fig. 3(b) that the real distances are far different from the estimated distances. Thus, to reduce the localization error related to the deviation, the deviation must have to be minimized. The random variable $S_D(0,\sigma^2_{RSS})$ has a normal distribution with zero mean and standard deviation σ_{RSS}. Thus, we can model the mean or linearized path loss as below

$$\begin{pmatrix} S_{PL}(d_1)_{lin} \\ S_{PL}(d_2)_{lin} \\ \vdots \\ S_{PL}(d_m)_{lin} \end{pmatrix} = \begin{pmatrix} 1 & 10\log_{10}(d_1/d_0) \\ 1 & 10\log_{10}(d_2/d_0) \\ \vdots & \vdots \\ 1 & 10\log_{10}(d_m/d_0) \end{pmatrix} \begin{pmatrix} S_{PL}(d_0) \\ \alpha \end{pmatrix}. \quad (6)$$

In Fig. 3(a), the solid line through the scattered path loss best fits the collected data. The solid line depicts the mean or linearized path loss which is obtained by minimizing the deviations using Eq. 6.

IV. Traditional Weighted Centroid Localization

Traditionally, WCL is a localization algorithm which finds the location of the target as weighted average of the sensors position as

Estimated position:

$$E_m(x,y,z) = \frac{\sum_{i=1}^{N}(W_{i,m}B_i(x,y,z))}{\sum_{i=1}^{N}W_{i,m}}, \quad (7)$$

where, $W_{i,m}$ is the weight of i^{th} sensor for m^{th} position of the target. For traditional WCL, weight is inversely proportional to distance,

$$W_{i,m} = \frac{1}{d_{i,m}}. \quad (8)$$

V. Performance Indices

We verify the localization accuracy using performance indices such as LE, ALE, STD.

LE at $m-$th location of capsule is the difference between estimated and real positions and can be represented as,

$$\begin{aligned} LE_m &= \sqrt{(P_m - R_m)^2} \\ &= \sqrt{(x_e - x_r)^2 + (y_e - y_r)^2 + (z_e - z_r)^2}, \quad (9) \end{aligned}$$

where, P_m is the estimated position using proposed algorithm and R_m is the real position of the capsule. (x_e, y_e, z_e) is the co-ordinate of the estimated position and (x_r, y_r, z_r) is the co-ordinate of the real position.

ALE is calculated as

$$ALE = \frac{\sum_{m=1}^{M} LE_m}{M}, \quad (10)$$

where, M is the number of capsule positions considered to compute ALE.

The STD is expressed as

$$STD = \sqrt{\frac{\sum_{m=1}^{M}(LE_m - ALE)^2}{M}}, \quad (11)$$

where, M is the number of capsule positions considered to compute STD.

The normalized error (%) is found as follows,

$$\text{Normalized error } (\%) = \frac{ALE}{\sqrt{(d_{max} - d_{min})^2}}, \quad (12)$$

where d_{max} is the maximum range in x-y-z direction and d_{min} is the minimum range in x-y-z direction.

VI. Proposed Localization Algorithm

In this paper, we propose two algorithms for localizing the capsule using static and dynamic degree based WCL. We propose optimal and sub-optimal methods of degree calculation. In our proposed WCL approach, the distance of the sensor and capsule (Tx-Rx) is used to calculate the weight of the sensors position. We raise the distance to a higher degree to consider the weight, $W_{i,m}$ of the sensors position at longer distances marginally lower and find the position P_m using WCL as

$$\begin{aligned} W_{i,m} &= \frac{1}{(d_{i,m})^g}, && (13) \\ P_m(x_e, y_e, z_e) &= \frac{\sum_{i=1}^{N} (W_{i,m} B_i(x_i, y_i, z_i))}{\sum_{i=1}^{N} W_{i,m}} \\ &= \frac{\sum_{i=1}^{N} \left(\frac{1}{(d_{i,m})^g} B_i(x_i, y_i, z_i) \right)}{\sum_{i=1}^{N} \frac{1}{(d_{i,m})^g}}, && (14) \end{aligned}$$

where, g is the degree which may be static or dynamic and B_i is the fixed known position of the sensor nodes. The proposed two methods of localization using optimal and sub-optimal degree are shown in Algorithm 1 and Algorithm 2, respectively. The detail steps of development of the algorithms are explained in the following.

A. Distance calculation

We calculate distance $d_{i,m}$ of the m^{th} position of target from the i^{th} sensor using adaptively linearized path loss (Eq. 6)

$$d_{i,m} = d_0 \times 10^{\frac{S_{PL}(d_{i,m})_{lin} - S_{PL}(d_0)}{10\alpha}}. \quad (15)$$

B. Degree calculation

We propose the following two methods of degree calculation using optimal and sub-optimal approach, respectively.

1) Optimal method: The proposed optimal method of degree calculation for both static and dynamic cases is based on minimizing the mean square error (MSE). In traditional WCL algorithm, the estimated position is as shown in Eq. 7. Normalizing the weight of the 8 sensors, we can express the estimated position of the capsule obtained from traditional WCL as

$$E_m(x, y, z) = \frac{\sum_{i=1}^{N} (\frac{1}{d_{i,m}} B_i(x, y, z))}{8}. \quad (16)$$

$\sum_{i=1}^{N} \frac{1}{d_{i,m}}$ is a Riemanns' zeta function and $\sum_{i=1}^{N} \frac{B_i(x,y,z)}{d_{i,m}}$ is a multiplicative Dirichlet series of the function $B_i(x, y, z)$ [35]. Expanding E_m into an Euler product [35], we obtain

$$\begin{aligned} E_m(x, y, z) &= \frac{\prod_{i=1}^{N} \left(1 + \sum_{k=1}^{\infty} \frac{B_i(x,y,z)}{(d_{i,m})^k}\right)}{8} \\ &= \frac{\prod_{i=1}^{N} \left(1 - \frac{B_i(x,y,z)}{d_{i,m}}\right)^{-1}}{8}. && (17) \end{aligned}$$

Taking logarithm on Eq. 17 yields

$$\log_{10} E_m(x, y, z) = \frac{\log_{10} \prod_{i=1}^{N} \left(1 - \frac{B_i(x,y,z)}{d_{i,m}}\right)^{-1}}{8}. \quad (18)$$

Now applying Merten's prime number theorem [35] on Eq. 18, we obtain the following Dirichlet series

$$\begin{aligned} \frac{\log_{10} \prod_{i=1}^{N} \left(1 - \frac{B_i(x,y,z)}{d_{i,m}}\right)^{-1}}{8} &= \frac{\sum_{i=1}^{N} \sum_{k=1}^{\infty} \frac{B_i(x,y,z)}{k(d_{i,m})^k}}{8} \\ &= \frac{\sum_{i=1}^{N} \frac{B_i(x,y,z)}{d_{i,m}} + O(1)}{8}, && (19) \end{aligned}$$

where $\frac{B_i(x,y,z)}{d_{i,m}}$ is the main term and $O(1)$ is an error term. Replacing k with g in Eq. 19, we obtain

$$\frac{\sum_{i=1}^{N} \frac{B_i(x,y,z)}{g(d_{i,m})^g}}{8} = \frac{\sum_{i=1}^{N} \frac{B_i(x,y,z)}{d_{i,m}}}{8} + \frac{O(1)}{8}. \quad (20)$$

From Eqs. 7, 14 and 20, we can write

$$\frac{1}{g} P_m = E_m + \frac{O(1)}{8}. \quad (21)$$

Equation 21 can be rewritten as

$$P_m = g E_m + g \frac{O(1)}{8}. \quad (22)$$

Finally, g can be approximated from Eq. 22 as

$$g \approx \frac{P_m}{E_m}. \quad (23)$$

Now, the problem of determining the optimal degree g_{opt} minimizing MSE is formulated as follows,

$$\begin{aligned} \text{Determine:} \quad & g_{opt} \\ \text{To Minimize:} \quad & MSE = \frac{\sum_{m=1}^{M} {LE_m}^2}{M} \end{aligned} \quad (24)$$

where, m is the number of locations and LE_m is the localization error for m^{th} position. Differentiating MSE with respect to g, we find

$$
\begin{aligned}
\frac{d(MSE)}{dg} &= \frac{d}{dg}\frac{\sum_{m=1}^{M} LE_m{}^2}{M} \\
&= \frac{1}{M}\sum_{m=1}^{M}\frac{d}{dg}(P_m - R_m)^2 \\
&= \frac{1}{M}\sum_{m=1}^{M}\frac{d}{dg}\left(\frac{\sum_{i=1}^{N}(W_{i,m}B_i)}{\sum_{i=1}^{N} W_{i,m}} - R_m\right)^2 \\
&= \frac{1}{M}\sum_{m=1}^{M}\frac{d}{dg}\left(\frac{\sum_{i=1}^{N}\left(\frac{1}{(d_{i,m})^g}B_i\right)}{\sum_{i=1}^{N}\frac{1}{(d_{i,m})^g}} - R_m\right)^2 \\
&= \frac{2}{M}\sum_{m=1}^{M}\left(\frac{\sum_{i=1}^{N}\left(\frac{1}{(d_{i,m})^g}B_i\right)}{\sum_{i=1}^{N}\frac{1}{(d_{i,m})^g}} - R_m\right) \\
&\quad \frac{d}{dg}\left(\frac{\sum_{i=1}^{N}\left(\frac{1}{(d_{i,m})^g}B_i\right)}{\sum_{i=1}^{N}\frac{1}{(d_{i,m})^g}}\right).
\end{aligned}
\tag{25}
$$

Equating first derivative to zero yields

$$\frac{\sum_{i=1}^{N}\left(\frac{1}{(d_{i,m})^g}B_i\right)}{\sum_{i=1}^{N}\frac{1}{(d_{i,m})^g}} - R_m = 0. \tag{26}$$

Equation 26 can be rearranged as

$$\frac{\sum_{i=1}^{N}\left(\frac{1}{(d_{i,m})^g}B_i\right)}{\sum_{i=1}^{N}\frac{1}{(d_{i,m})^g}} = R_m. \tag{27}$$

From Eqs. 14 and 27, we can write

$$P_m = R_m; \quad \text{for } m = 1, 2, 3, \cdots, M \tag{28}$$

Thus, the mean localization error is minimum when the estimated position using the proposed algorithm (P_m) is equal to the real positions of the target (R_m). By replacing the value of P_m as R_m into Eq. 23, the optimal value of g can be written as

$$g \approx \frac{R_m}{E_m}. \tag{29}$$

Using the obtained value of g in Eq. 29, we can calculate the static and dynamic degree as below.

Static optimal degree

Applying linear least square (LLS) regression of the estimated and real positions, finally the static optimal degree g_{sopt} is obtained as

$$g_{sopt} = (EE^T)^{-1}RE^T. \tag{30}$$

Dynamic optimal degree

We can consider the dynamic optimal degree g_{dopt} using the recent update of positions as

$$g_{dopt_m} = \frac{R_m}{E_m}; \quad \text{for } m = 1, 2, 3, \cdots, M. \tag{31}$$

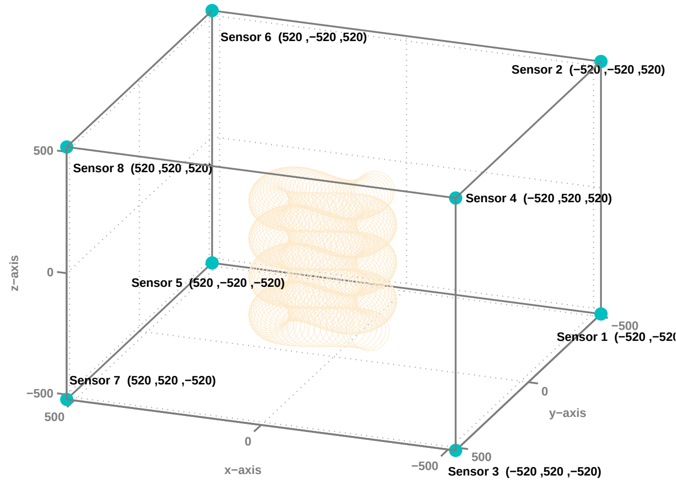

Fig. 4. Simulation system including sensor array of 8 receiver and signal propagation model of small intestine.

2) Sub-optimal method: The proposed sub-optimal methods for determining both static and dynamic degrees are presented below.

Static sub-optimal degree

We propose a method of computing static sub-optimal degree g_{ssopt} using the logarithm of the maximum distance d_{max} as

$$g_{ssopt} = \log_{10}(d_{max}). \tag{32}$$

Dynamic sub-optimal degree

The dynamic sub-optimal degree is calculated using the recent updated location of the target. As the target capsule transmitter moves through the GI tract, the Tx-Rx separation distance also changes. We calculate the updated dynamic distance $d_{i,m}$ using Eq. 15 which is then used to calculate the sub-optimal degree. The proposed dynamic sub-optimal degree g_{dsopt} is calculated as

$$g_{dsopt} = \log_{10}\left(\frac{d_{i,m}}{d_{min}}\right), \tag{33}$$

where $d_{min} < d_{i,m}$. In summary, the optimal methods of degree calculation is dependent on the real positions of capsule. Whereas, the sub-optimal methods do not require to know the real positions as a prior. Since the dimension of the sensor network and the dimension of the region of interest (ROI) are fixed, the maximum covered range d_{max} and the minimum distance d_{min} are known values. Thus, it is realistic to calculate the degree using sub-optimal methods.

C. Position estimation

This is the final step of position estimation using static and dynamic degree based WCL. Here we estimate the position of the capsule by replacing the value of the estimated degree in Eq. 14.

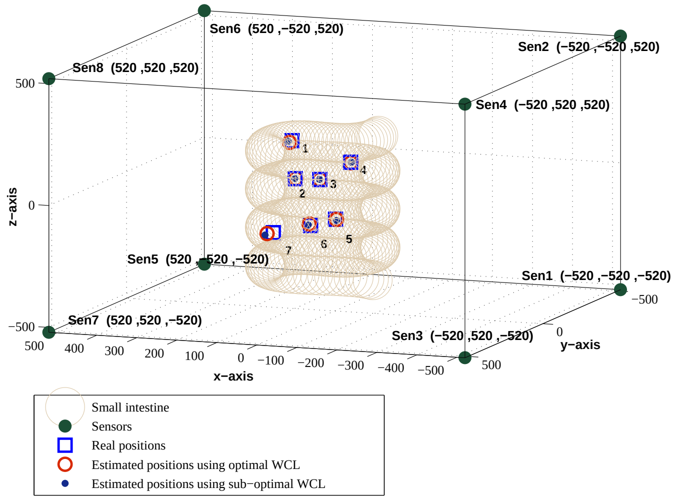

Fig. 5. Simulation results using static degree based WCL.

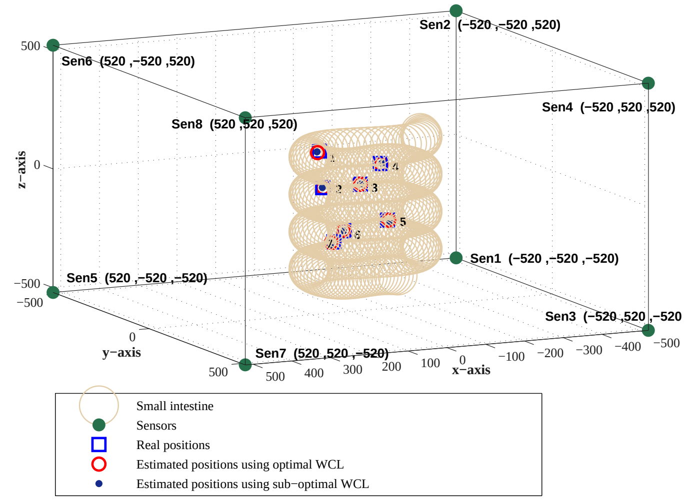

Fig. 6. Simulation results using dynamic degree based WCL.

TABLE III

REAL AND ESTIMATED POSITIONS USING STATIC DEGREE BASED WCL

Real positions, $R_m(x_r, y_r, z_r)$	Estimated positions using optimal degree $P_m(x_e, y_e, z_e)$	Estimated positions using sub-optimal degree $P_m(x_e, y_e, z_e)$
(95, 30, 177)	(100.2, 33.2, 169.9)	(103.3, 34.2, 174.6)
(87, 31, 22)	(85.3, 31.3, 22.3)	(87.7, 32.2, 22.9)
(9.9, 72.9, 37.5)	(9.9, 71.8, 37.6)	(10.2, 73.9, 38.7)
(-56, 43, 107)	(-57.2, 44.2, 105.2)	(-58.9, 45.5, 108.2)
(-43, 109, -110)	(-45.5, 109.7, -110.6)	(-46.9, 112.8, -113.8)
(41, 51, -160)	(43.6, 54, -153)	(44.9, 55.6, -157.2)
(105, 129, -175)	(116.8, 139.1, -177)	(120.4, 143.3, -182.1)

TABLE IV

REAL AND ESTIMATED POSITIONS USING DYNAMIC DEGREE BASED WCL

Real positions, $R_m(x_r, y_r, z_r)$	Estimated positions using optimal degree $P_m(x_e, y_e, z_e)$	Estimated positions using sub-optimal degree $P_m(x_e, y_e, z_e)$
(95, 30, 177)	(101.5, 33.6, 171.8)	(102.9, 33.9, 175.8)
(87, 31, 22)	(86.2, 31.7, 22.5)	(88.6, 32.4, 23.1)
(9.9, 72.9, 37.5)	(10.1, 72.5, 37.9)	(10.3, 74.6, 39)
(-56, 43, 107)	(-57.6, 44.5, 105.9)	(-59.1, 45.7, 109.1)
(-43, 109, -110)	(-45.58, 109.78, -110.68)	(-46.83, 113.34, -114.28)
(41, 51, -160)	(44.4, 55, -155.6)	(44.8, 55.5, -158.6)
(105, 129, -175)	(114.6, 136.5, -174)	(118.6, 141.8, -181.5)

In next section, we will see the performances of the proposed algorithms.

VII. SIMULATION AND RESULTS

In this section, we simulate the proposed static and dynamic degree based VCE localization algorithms to evaluate the performance and to compare the accuracy. As it is not possible to validate the performance using real human body, we develop a $3D$ visualization platform using MATLAB to show the results and to verify the performance. The simulation platform includes the statistics of the path loss model of deep tissue implant to body surface scenario [22] to consider real characteristics of human body channel as shown in Eq. (6). It also includes a small intestine model with its position map and a sensor array of eight receivers with their reference positions as shown in Fig. 4. The sensors are placed at eight corner points of the sensor array. We simulate our proposed static and dynamic degree based algorithms for different dimension of the sensor network to localize the VCE in small intestine of $280mm \times 240mm \times 360mm$ dimension. The simulation platform shows the estimated positions as well as the real positions in the same platform and evaluates the accuracy using different performance indices as follows

A. Performance of static degree based WCL

We simulate the static degree based WCL algorithm using both optimal and sub-optimal degree to verify and compare the performance using a sensor network of $1040mm \times 1040mm \times 1040mm$ dimension for 2530 possible target positions inside the small intestine. The information flow of the optimal and sub-optimal method of degree calculation using static degree are shown as in Fig. 7 and Fig. 8, respectively. Figure 5 shows the simulation results of the proposed static degree based WCL for seven sample target positions and compares the accuracy of the sub-optimal methods to the optimal. The results are summarized in Table III. As we can see from the results that the accuracy of the proposed sub-optimal methods comply to the optimal benchmark accuracy and the estimated positions are in good agreement with the real positions.

B. Performance of dynamic degree based WCL

We simulate dynamic degree based WCL using both optimal and sub-optimal degree for 2530 possible target positions inside the small intestine using $1040mm \times 1040mm \times 1040mm$ dimension of the sensor network. The information flow of the dynamic degree based WCL using optimal and sub-optimal degree are shown in Fig. 7 and Fig. 9, respectively. The simulation results for seven sample positions are shown in

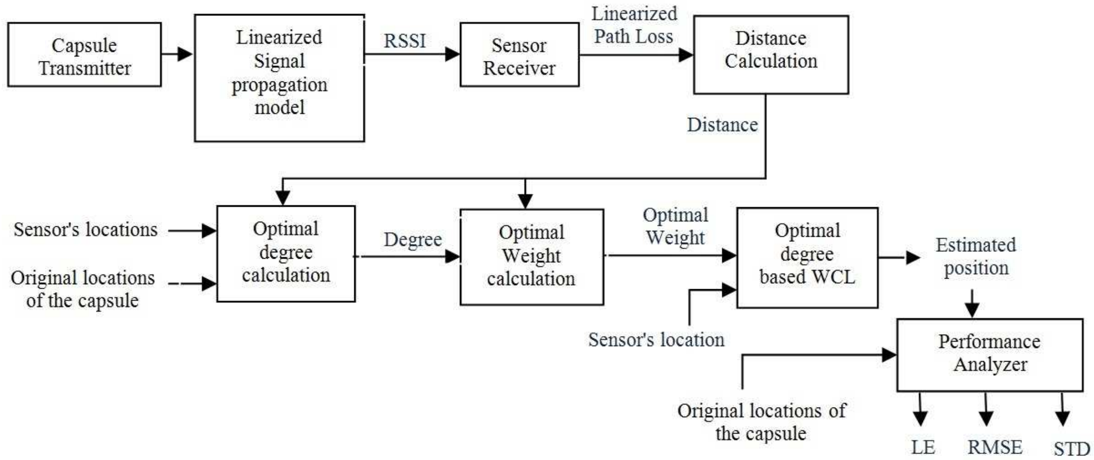

Fig. 7. Information flow of optimal degree (both static and dynamic) based WCL.

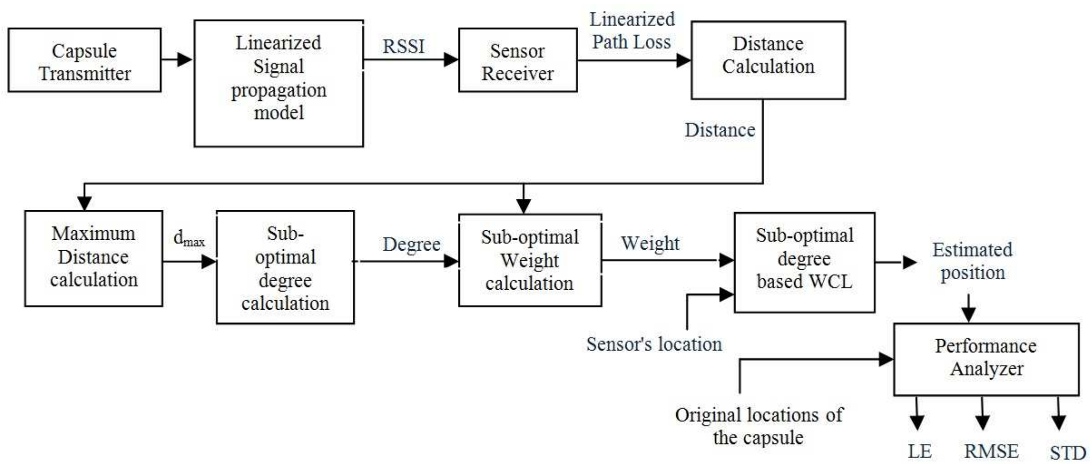

Fig. 8. Information flow of sub-optimal static degree based WCL.

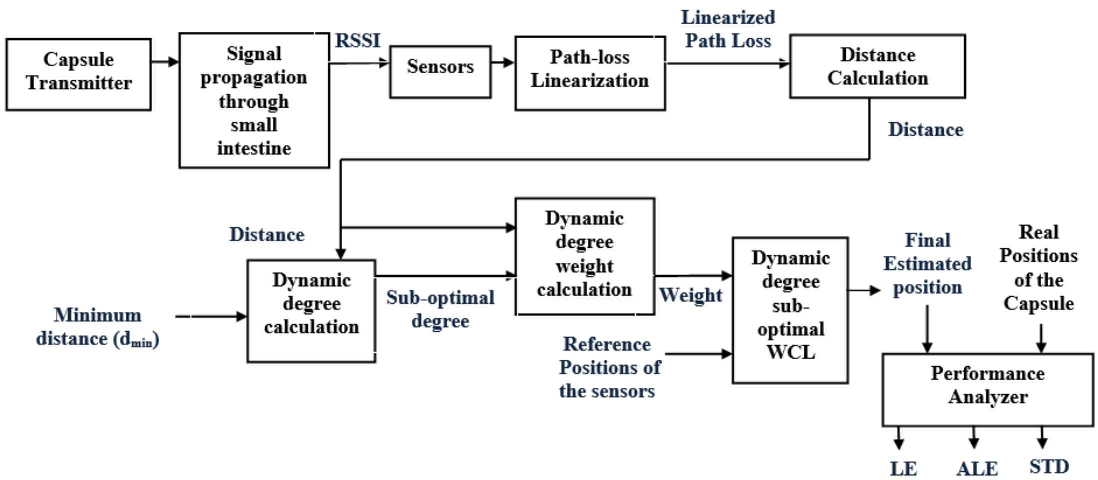

Fig. 9. Information flow of sub-optimal dynamic degree based WCL.

TABLE V

ACCURACY OF DIFFERENT OPTIMIZATION METHODS FOR DIFFERENT DIMENSION OF THE NETWORK

Average Localization Error (ALE, in mm) for traditional and proposed WCL							
Sensor network dimension (in mm)	Calibration method [30]	Traditional $W = \frac{1}{(S_{PL})_{lin}}$	Traditional $W = \frac{1}{d}$	Static optimal $W = \frac{1}{d^{g_{sopt}}}$ (Benchmark)	Static sub-optimal $W = \frac{1}{d^{g_{ssopt}}}$ (Proposed)	Dynamic optimal $W = \frac{1}{d^{g_{dopt}}}$ (Benchmark)	Dynamic sub-optimal $W = \frac{1}{d^{g_{dsopt}}}$ (Proposed)
$600 \times 600 \times 600$	5.15	138.6	98.2	14.99	11.11	10.19	12.07
$680 \times 680 \times 680$	6.3	138.86	98.43	11.8	11.82	8.27	9.61
$760 \times 760 \times 760$	2.93	139.08	98.52	9.54	9.54	6.8	7.9
$840 \times 840 \times 840$	2.33	139.36	98.7	7.86	8.03	5.6	6.8
$920 \times 920 \times 920$	1.9	139.42	98.78	6.59	7.07	4.79	6.3
$1000 \times 1000 \times 1000$	1.58	139.57	98.84	5.6	6.6	4.1	6.1
$1040 \times 1040 \times 1040$	1.45	139.6	98.87	5.19	6.55	3.8	6.27
$1080 \times 1080 \times 1080$	1.33	139.7	98.89	4.82	6.59	3.54	6.46
$1120 \times 1120 \times 1120$	1.23	139.76	98.91	4.49	6.75	3.3	6.73
$1200 \times 1200 \times 1200$	1.06	139.87	98.94	3.92	7.32	2.89	7.45
$1280 \times 1280 \times 1280$	0.92	139.97	98.97	3.45	8.10	2.55	8.26

TABLE VI

COMPARISON OF LOCALIZATION ACCURACY

System	**Algorithm/ method**	**Information basis**	**ALE**	**STD**	**Normalized error (%)**	**No. of sensors**	**Dimension**
Chandra et al. [25] RF localization	LLS method and non LLS method	Radio signal	10 mm	-	14.14%	8	$2D$
Arshak and Adepoju [27] RF localization	Linear approximation of RSSI and trilateration	Linear approximated RSSI	25 mm	-	25%	3	$2D$
Mohammad et al. [28] RF localization	Convex optimization theory	TOA and signal strength	15 mm	15 mm	12.21%	16	$2D$
Wang et al. [29] RF localization	RSS Triangulation	RSSI signal	48 mm	-	16.25%	32	$2D$
Hany and Wahid [30] RF localization	Adaptively linearized LLS WCL	Linearized RSSI and Real positions	5.15 mm	3.5 mm	1.16%	8	$3D$
Optimal static degree based RF localization (benchmark)	LLS based static degree optimal WCL	Linearized RSSI and Real positions	5.19 mm	4.18 mm	1.1%	8	$3D$
Sub-optimal static degree based RF localization (proposed)	Maximum range based Static degree sub-optimal WCL	Linearized RSSI	6.55 mm	6.61 mm	1.43%	8	$3D$
Optimal dynamic degree based RF localization (benchmark)	Recent update based dynamic degree optimal WCL	Linearized RSSI and Real positions	3.8 mm	3.14 mm	0.805%	8	$3D$
Sub-optimal dynamic degree based RF localization (proposed)	Recent update based dynamic degree sub-optimal WCL	Linearized RSSI	6.27 mm	5.96 mm	1.32%	8	$3D$

Fig. 6 and summarized in Table IV. As we can see that the accuracy of the proposed sub-optimal methods are very close the optimal benchmark accuracy and the estimated positions are in good agreement with the real positions.

C. Comparison

We simulate the proposed algorithms and compare the results for different dimension of network as shown in Table V. The results show that the calibration process [30] improves the accuracy to certain level. However, as the calibration process requires real positions to find the calibration co-efficient, it is not practically implementable. We also observe that the localization accuracy is improved when a degree is applied to the distance. The results of the proposed degree based methods are presented and compared in Table III, IV and V which clearly shows significant improvement using proposed static and dynamic degree based methods. It also shows that the optimal benchmark accuracy is possible to be achieved using our proposed sub-optimal methods (both static and dynamic). The weight, W calculated using static and dynamic degree are plotted as a function of distance in Fig. 10 and Fig. 11, respectively. As we can see from Figs. 10 and 11 that using both methods, the lower distance sensors are more weighted than the higher distance sensors. We can also observe that the calculated weights using optimal and sub-optimal degree are very close to each other. Figure 12 and 13 shows the estimated positions of few target positions compared to the real positions using static and dynamic degree based methods.

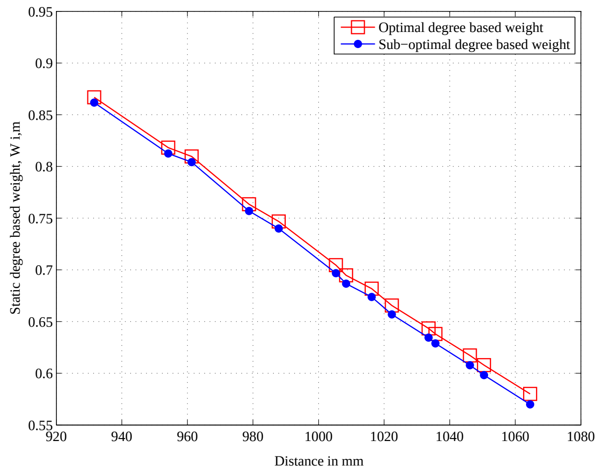

Fig. 10. Static degree based Weight as a function of Distance.

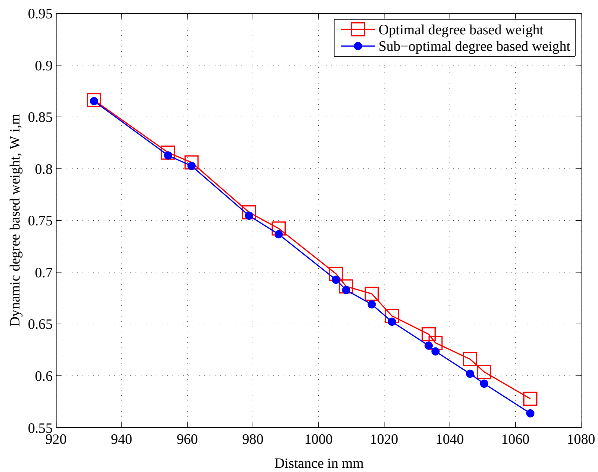

Fig. 11. Dynamic degree based Weight as a function of Distance.

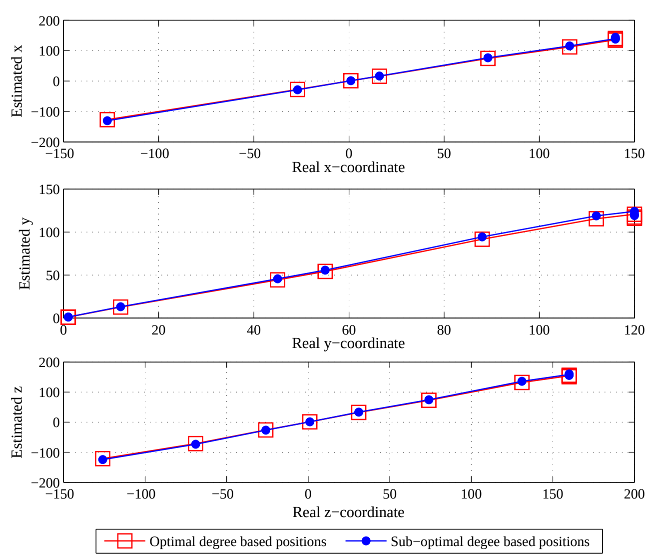

Fig. 12. Comparison of the estimated and real positions for static degree based WCL.

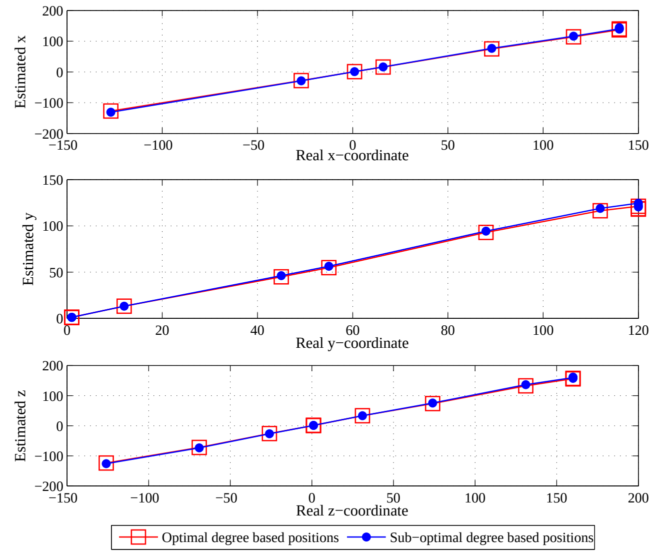

Fig. 13. Comparison of the estimated and real positions for dynamic degree based WCL.

As we can observe from Figs. 12 and 13 that the positions estimated using both optimal and sub-optimal degree are very close to each other. It is also observed that the estimated positions using proposed methods are in good agreement with the real positions. Table V shows that the dynamic degree based (both optimal and sub-optimal) methods improve the localization accuracy (i.e., lower ALE) and Table VI shows that it also reduces the standard deviation of error. However, as the real positions are required to be known to calculate the optimal degree, it is not practically implementable, rather it is computed analytically to compare the performance of sub-optimal method. The proposed sub-optimal methods are realistic as they approach the benchmark accuracy without any prior knowledge of real positions or any calibration process as in [30].

Table V also presents the performance of the proposed localization algorithms for several dimension of sensor network. In each case, we observe that proposed methods perform equally well. It is also to be noted from Table V that using our proposed methods, the localization error decreases with increase of dimension (x-y-z axis). With the increase of dimension, the target's location rationally approaches to the center (0,0,0) of the network. As WCL finds the weighted average of the sensors location, it can find the target's location more accurately when the target approaches to the center of the network. The static sub-optimal method shows best performance for $1040mm \times 1040mm \times 1040mm$ dimension of the network, whereas dynamic sub-optimal method shows best performance for $1000mm \times 1000mm \times 1000mm$ dimension of the network.

There are different RF localization algorithms based on triangulation or other methods available in the literature [25]-[29]. The mean localization error of those methods are within $10-50\ mm$. Table VI compares the localization accuracy of those methods in terms of different performance indices and shows better performance of our proposed algorithms. As compared to other works, our proposed sub-optimal methods show improved localization accuracy without any prior knowledge of real positions.

VIII. Conclusion

In this paper, we have proposed static and dynamic degree based WCL algorithms for video endoscopic capsule localization while it travels through the small intestine. We have proposed sub-optimal method of degree calculation for both static and dynamic cases. We have also analytically computed the optimal value of the degree to set benchmark for the accuracy of the proposed sub-optimal methods. We have developed a $3D$ visualization platform using MATLAB to simulate and evaluate the performance of the proposed localization algorithms considering real characteristic of human body channel. We have observed that optimal benchmark accuracy is possible to be achieved using our proposed sub-optimal methods even when we change the dimension of the sensor network. We have compared the performance of our proposed algorithms to other works to validate the performance and observed significant improvement over the present literature.

Algorithm 1 Static and dynamic degree based optimal WCL

Input: $R,\ P_T,\ RSSI,\ d_0,\ B_i(x_i, y_i, z_i)[\ \forall i]$
Output: $E,\ P_s,\ P_d$
for $m = 1,\ 2, \cdots,\ M$ **do**
  for $i = 1,\ 2, \cdots,\ N$ **do**
    {% distance calculation using linearized path loss}
    $S_{PL}(d_{i,m})_{lin} = P_T - RSSI_{i,m}$
    $S_{PL}(d_{i,m})_{lin} = S_{PL}(d_0) + 10\alpha \log_{10}\left(\frac{d_{i,m}}{d_0}\right)$
    $d_{i,m} = d_0 10^{\frac{S_{PL}(d_{i,m})_{lin} - S_{PL}(d_0)}{10\alpha}}$
    {% linear weight calculation}
    $W_{i,m} = \frac{1}{d_{i,m}}$
  end for
  {% estimated positions using linear WCL}
  $E_m(x_e, y_e, z_e) = \frac{\sum_{i=1}^{N}(W_{i,m} B_i(x_i, y_i, z_i))}{\sum_{i=1}^{N} W_{i,m}}$
  {% dynamic optimal degree}
  $g_{(dopt)_m} = \frac{R_m}{E_m}$
end for
{% static optimal degree}
$g_{sopt} = (EE^T)^{-1} RE^T$
for $m = 1,\ 2, \cdots,\ M$ **do**
  for $i = 1,\ 2, \cdots,\ N$ **do**
    {% static optimal weight}
    $W_{(i,m)_{sopt}} = \frac{1}{(d_{i,m})^{g_{sopt}}}$
    {% dynamic optimal weight}
    $W_{(i,m)_{dopt}} = \frac{1}{(d_{i,m})^{g_{dopt_m}}}$
  end for
  {% positions using static degree optimal WCL}
  $P_s(x_e, y_e, z_e) = \frac{\sum_{i=1}^{N}\left(W_{(i,m)_{sopt}} B_i(x_i, y_i, z_i)\right)}{\sum_{i=1}^{N} W_{(i,m)_{sopt}}}$
  {% positions using dynamic degree optimal WCL}
  $P_d(x_e, y_e, z_e) = \frac{\sum_{i=1}^{N}\left(W_{(i,m)_{dopt}} B_i(x_i, y_i, z_i)\right)}{\sum_{i=1}^{N} W_{(i,m)_{dopt}}}$
end for

Algorithm 2 Static and dynamic degree based sub-optimal WCL

Input:$P_T,\ RSSI, ,\ d_0,\ d_{max},\ d_{min},\ B_i(x_i, y_i, z_i)[\ \forall i]$
Output: $P_s,\ P_d$
for $m = 1,\ 2, \cdots,\ M$ **do**
  for $i = 1,\ 2, \cdots,\ N$ **do**
    {% distance calculation using linearized path loss}
    $S_{PL}(d_{i,m})_{lin} = P_T - RSSI_{i,m}$
    $S_{PL}(d_{i,m})_{lin} = S_{PL}(d_0) + 10\alpha \log_{10}\left(\frac{d_{i,m}}{d_0}\right)$
    $d_{i,m} = d_0 10^{\frac{S_{PL}(d_{i,m})_{lin} - S_{PL}(d_0)}{10\alpha}}$
    {% static sub-optimal degree}
    $g_{ssopt} = \log_{10}(d_{max})$
    {% dynamic sub-optimal degree}
    $g_{dsopt_m} = \log_{10}(d_{i,m} - d_{min})$
    {% static sub-optimal weight}
    $W_{(i,m)_{ssopt}} = \frac{1}{(d_{i,m})^{g_{ssopt}}}$
    {% dynamic sub-optimal weight}
    $W_{(i,m)_{dsopt}} = \frac{1}{(d_{i,m})^{g_{dsopt_m}}}$
  end for
  {% positions using static degree sub-optimal WCL}
  $P_{m_s}(x_e, y_e, z_e) = \frac{\sum_{i=1}^{N}\left(W_{(i,m)_{ssopt}} B_i(x_i, y_i, z_i)\right)}{\sum_{i=1}^{N} W_{(i,m)_{ssopt}}}$
  {% positions using dynamic degree sub-optimal WCL}
  $P_{m_d}(x_e, y_e, z_e) = \frac{\sum_{i=1}^{N}\left(W_{(i,m)_{dsopt}} B_i(x_i, y_i, z_i)\right)}{\sum_{i=1}^{N} W_{(i,m)_{dsopt}}}$
end for

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