Accurate tumor localization and tracking in radiation therapy using wireless body sensor networks

Mohammad Pourhomayoun³, Zhanpeng Jin⁴,⁵,⁶, Mark Fowler⁷

Abstract

Radiation therapy is an effective method to combat cancerous tumors by killing the malignant cells or controlling their growth. Knowing the exact position of the tumor is a very critical prerequisite in radiation therapy. Since the position of the tumor changes during the process of radiation therapy due to the patient's movements and respiration, a real-time tumor tracking method is highly desirable in order to deliver a sufficient dose of radiation to the tumor region without damaging the surrounding healthy tissues.

In this paper, we develop a novel tumor positioning method based on spatial sparsity. We estimate the position by processing the received signals from only one implantable RF transmitter. The proposed method uses less number of sensors compared to common magnetic transponder based approaches. The performance of the proposed method is evaluated in two different cases: (1) when the tissue configuration is perfectly determined (acquired beforehand by MRI or CT) and (2) when there are some uncertainties about the tissue boundaries. The results demonstrate the high accuracy and performance of the proposed method, even when the tissue boundaries are imperfectly known.

1. Introduction

1.1. Problem description

Radiation therapy (also called Radiotherapy) is an effective method to combat cancerous tumors by delivering high doses of radiation to the tumor to kill or control the growth of malignant cells by damaging their DNA [1]. A critical requirement of radiation therapy is to precisely delineate tumors and adjacent normal structures to avoid healthy tissues exposed under radiation. Recent specialized CT and/or MRI assisted techniques, such as three-dimensional conformal radiation therapy (3DCRT) and Intensity-Modulated Radiation Therapy (IMRT) [24], have significantly enhanced the ability to deliver an accurate radiation dose to the target volumes. In these methods, the radiation is split into hundreds of thin beamlets targeting the tumor from various angles to achieve a better focus on the cancerous region and reduce the damage to the surrounding healthy tissues [2]. In IMRT, beamlets can also have various radiation intensities and it helps to produce a treatment area that better conforms to the contour of the tumor [3].

Knowing the exact position of the tumor is one of the most essential prerequisites in radiation therapy, because any slight bias in the position of the tumor will cause the radiation to be delivered to the surrounding healthy tissues rather than the tumor area, which would not only degrade the performance of the treatment due to a lack of sufficient dose for the tumor treatment, but also may cause severe side effects such as tissue toxicity and secondary cancer [2,4]. It is important to note that the position of the tumor changes during radiation therapy because of respiration, gastro-intestinal, bladder filling, cardiac system or patient movements. Thus a real-time tumor tracking mechanism is highly desired in radiation therapy treatments in order to deliver and maintain a precise amount of radiation to the tumor region without damaging the surrounding healthy tissues [2,4].

1.2. Background and previous work

Various methods have been proposed in the literature for tumor tracking in radiation therapy treatments based on implanting several wired or wireless devices (called beacons) inside or in the vicinity of the tumor [2–13]. The Calypso localization system is one of the most prevalent methods that has been widely used for tumor positioning in prostate radiation therapy [7,8]. In the Calypso system, three magnetic transponders are implanted inside...
or in the vicinity of the target. Localization of the transponders is achieved using an electromagnetic array consisting of four electromagnetic coils to excite the transponders and 32 receiving coils to pick up the response from the transponders. Positions of the implanted transponders are estimated relative to the magnetic array based on the response measurements [4,7]. There are several other electromagnetic based localization systems such as the 3-dimensional magnetic tracking methods as proposed in [2,13] that use the similar idea to track the tumor positions during the radiation therapy.

Infrared camera with external marker has been also used for tumor tracking. In this method, the simultaneous motions of several external markers and an internal target are estimated using an infrared camera system [25–28]. Recently, radar sensor systems have also been attracting extensive attention for the purpose of tumor tracking [29–31].

1.3. The proposed approach

In this paper, we propose and develop a novel positioning method based on spatial sparsity in 3D space and convex optimization theory [17] to achieve accurate results. In the proposed method, we use only one wireless implantable RF transmitter implanted inside or in the vicinity of the tumor. The implant plays the role of an emitter by transmitting an RF signal. The signal will be received by a sensor array mounted in a known position beneath or above the patient’s body. Then, the received signals will be processed to estimate the position of the implant (i.e., the emitter) relative to the sensor array, based on received signal strength (RSS), time-of-arrival (TOA), and phase shift parameters.

The classical localization methods usually include two stages. In the first stage, one or more location-dependant parameters (such as TOA or RSS) are estimated. Then in the second stage, these parameter estimates are used in statistical processing or finger printing methods to estimate the location of target. However, the classic two-stage method is not necessarily optimal because in the first stage the parameter estimates are obtained by ignoring the fact that all measurements should be consistent with a single target location. In other words, each stage itself is optimal but the cascade of the two stages is not necessarily optimal [14].

Unlike classic RSS or TOA based localization approaches, we use convex optimization theory to solve the problem of location estimation directly without going through the intermediate stage of TOA or RSS estimation. In other words, there is no need to explicitly estimate the RSS or TOA for each of the sensors in a separate stage and the decision about the target location is made directly based on all received signals. Given all aforementioned features, the proposed method is much more accurate in positioning and very robust to multipath conditions caused by signal reflections at the boundaries of body organs compared to classic TOA/RSS based methods.

Some serious challenges exist for the in-body localization, compared to regular localization in other environments. The human body is made up of various organs that consist of different types of tissues; thus, the electrical characteristics of the body – such as power absorption, conductivity and relative permittivity – show significant anisotropy and heterogeneity. For example, the relative permittivity value varies according to the tissue type. Since the signal propagation velocity is expressed as a function of the relative permittivity, the propagation velocity and consequently the TOA highly depends on the specific tissue layers that the signal passes through from the implant (emitter) to the sensor (receiver) [15]. The path loss exponent and power absorption parameters also vary by tissue thickness [18]. Therefore, traditional in-body localization methods based on RSS or TOA are challenging and sometimes inaccurate unless we have a priori knowledge about the position of the implant.

Even if this a priori information is available it is difficult to exploit it in the classical location methods. In this paper, we propose a novel tissue-adaptive approach, considering the propagation velocity and path loss exponent as location-dependent parameters that can be exploited to estimate the implant location more precisely.

In [15,16], we reported preliminary results for a proposed 2-dimensional positioning method based on spatial sparsity. However, those studies suffer from various assumptions made for the purpose of simplification and ease of implementation. For instance, in [15] the human body is assumed to be uniformly made by only one tissue type. In [16], we addressed the tissue variety problem by simply calculating the weighted average of relative permittivity and then computing the average propagation velocity. In this paper, to achieve more precise results, we first estimate the exact interconnection points between the line-of-sight and the tissue boundary surfaces. Then, the accurate delay will be calculated as the summation of delays in each tissue layer. We will also expand the results by providing a detailed discussion on how the path loss and delay should be computed for each potential signal path including the method developed to estimate the interconnection points between line-of-sight and tissue boundary surfaces. Furthermore, we will derive new equations and algorithms for the 3-dimensional localization.

The performance of the proposed approach was evaluated using Monte-Carlo computer simulation. The results demonstrate the high localization accuracy of our method (i.e., less than 2 mm error using only 4 receiver sensors), even in the case when the tissue configurations are not exactly known and the tissue boundaries are uncertain. The results also show the robustness of the proposed method to multipath conditions that are caused by massive signal reflections at the boundaries of human body organs.

The rest of the paper is organized as follows. In Section 2, we first give an overview of the concept of spatial sparsity, and how to achieve sparse solutions using convex optimization. Then, we discuss the received signals model and path-loss and TOA computation in human body consisting of various types of tissues. Next, we present the problem formulation and show how we exploit the sparsity and convex optimization theory to solve the location estimation problem based on both TOA and RSS. Then, we propose an alternative approach to reduce the computational complexity of the problem, especially for 3-dimensional localizations. In Section 3, we evaluate the performance of the proposed method in two different cases: when the tissue configuration and boundaries are exactly known, and when a certain level of ambiguity and uncertainty of the tissue configuration exists. Finally, we provide some discussions about the results and performance of the proposed method.

2. Methods: tumor localization and tracking

2.1. Spatial sparsity based approach

If we consider the human body area of interest as a fine enough three-dimensional grid space, the number of grid points containing the implant(s) (i.e., the emitters) is much smaller than the number of all grid points in the space. Assume that we allocate a positive number (such as one) to the grid points that include an emitter and assign zero to the rest of the grid points. Now, by arranging those numbers into a vector, we obtain a very sparse vector including only one (or more if we have more than one implant) non-zero element. Since each element of this long vector corresponds to a grid point in the grid space, we are able to estimate the location of the implant by finding the position of the non-zero elements of the sparse vector.

In general, the $\|v\|_p$-norm of a vector $v$ is defined as $\|v\|_p = \sqrt[p]{\sum |v_i|^p}$. In many optimization problems (such as the least square
problems), we aim to minimize the $\ell_2$-norm of a vector. However, $\ell_2$-norm minimization will not achieve the sparse solution because $\ell_2$-norm just measures the signal energy not the sparsity [17]. In principle, the sparse solution is obtained by minimizing the $\ell_0$-norm of a vector which is defined as the number of non-zero elements of the vector. Unfortunately, the $\ell_0$-norm minimization is an NP-hard non-convex optimization problem; thus we need to find an alternate solution. It is shown that $\ell_1$-norm minimization is a reasonable approximation for $\ell_0$-norm minimization problems; it achieves the sparse solution very well and it is a convex optimization problem that can be simplified to a linear program known as basis pursuit [17].

In our localization problem, we seek to find the sparse vector that maximizes the fit of the predicted received signals based on the estimated location and the true observed signals by sensors. In other words, we can estimate the location of emitter(s) by extracting the positions of those non-zero elements in the “sparest” vector that satisfies the delay and path lost relationship between transmitted signals (by implant) and observed signals (by sensors).

Thus, after formulating the problem in terms of the unknown sparse grid vector, we can estimate this vector by enforcing the sparsity using $\ell_1$-norm minimization on the grid vector, and at the same time minimizing the cost among expected received signals (that satisfy the delay and signal strength relationship) and actual received signals by forming a least square problem.

2.2. Signal model and parameters

Suppose that an implanted beacon transmits a signal and L sensors receive that signal. Then the complex baseband signal observed by the $i$th sensor is

$$ s_i(t) = a_i S_i(t - \tau_i) + n_i(t) $$

(1)

where $S_i(t)$ is the transmitted signal, $\tau_i$ is delay, $n_i(t)$ is the noise, and $a_i$ is the gain including path loss and a phase shift. $a_i$ can be written as

$$ a_i = \beta_i e^{j\phi_i} $$

where $\beta_i$ represents the real path loss, $\phi_i = -2\pi f_c \tau_i$ is constant phase, and $f_c$ is the carrier frequency.

The path loss model in dB is given by [18]

$$ P_{\text{loss}}(d) = P_{\text{loss}}(d_0) + 10\beta \log_{10}(d/d_0) + R $$

(2)

where $P_{\text{loss}}(d)$ is the path loss at distance $d$, $P_{\text{loss}}(d_0)$ is the path loss at the reference distance $d_0$, $\beta$ is the path loss exponent value and $R$ is a zero mean Gaussian random variable (in dB) representing the shadowing effect, $R \sim N(0, \sigma_R^2)$ [18]. Table 1 shows the path loss parameters for the path from implant to the body surface [18].

We have to note that the term $e^{j\phi_i} = e^{-j2\pi f_c \tau_i}$ includes important information about the signal phase and delay. This information can be very beneficial in location estimation, especially for narrowband signals where it is difficult or impossible to estimate the delay from the signal samples. Traditional TOA based localization methods usually do not exploit the term $\phi_i = -2\pi f_c \tau_i$ in location estimation, and that is why for narrowband signals (such as the signals we use for in-body localization), the traditional methods fail to achieve accurate results. However, in the proposed method, since we use the entire signal to estimate the location directly, we take advantage of this term to achieve much more accurate results.

<table>
<thead>
<tr>
<th>Implant to body surface</th>
<th>$P_{\text{loss}}(d_0)$ (dB)</th>
<th>$\beta$</th>
<th>$\sigma_R$ (dB)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Deep tissue</td>
<td>47.14</td>
<td>4.26</td>
<td>7.85</td>
</tr>
<tr>
<td>Near surface</td>
<td>49.81</td>
<td>4.22</td>
<td>6.81</td>
</tr>
</tbody>
</table>

In free space, we can reasonably assume that the signal propagation velocity is constant. However, this assumption will no longer be eligible for the scenario inside the human body, and the propagation velocity varies through different body tissue types. Consequently, the delay (TOA) relies on the specific tissue that the signal passes through. The signal propagation velocity $v(\omega)$ at a specific frequency in a homogeneous tissue is given by

$$ v = c V_F(\omega) $$

$$ V_F(\omega) = \frac{1}{\sqrt{\varepsilon_f \omega}} $$

(3)

where $c$ is the speed of light in the free space, $V_F(\omega)$ is velocity factor and $\varepsilon_f(\omega)$ is the relative permittivity of a human body tissue at frequency $\omega$. As we see in the above equation, the relative permittivity is frequency dependent. However, the curves and values of relative permittivity are available for various frequencies and different body tissues (such as fat, muscle, bone, lung, stomach, intestine, tendon and so on) [19–21].

In [16], we calculated the weighted average of relative permittivity (with percentage of each tissue on the overall path as weights) and the average velocity using Eq. (3), and then used this average velocity to obtain the delay for the entire path. In this paper, to achieve more precise results, we propose to calculate the overall delay in the following manner:

$$ \tau = \sum_{i=1}^{N_t} \frac{d_i}{v_i} = \frac{1}{\sum_{i=1}^{N_t} k_i \sqrt{\varepsilon_i}} $$

(4)

where $N_t$ is the number of different tissue layers on the path, $d_i$, $v_i$, and $\varepsilon_i$ are the delay, length, velocity and relative permittivity of ith tissue respectively (at desired frequency) and $k_i= (d_i/\|d\|)$ is the percentage of each tissue on the path. We can rephrase Eq. (4) as

$$ v_e = \frac{\sum_{i=1}^{N_t} k_i \sqrt{\varepsilon_i}}{\sum_{i=1}^{N_t} \sqrt{\varepsilon_i}} $$

(5)

where $v_e$ is the equivalent propagation velocity. We seek to estimate the equivalent signal propagation velocity $v_e$ for the paths from each grid point to the sensors. This estimation is accomplished by calculating the percentage of each tissue layer on the entire path. Note that this velocity estimation can be performed in an off-line manner given the configuration of the body tissue layers, which could be acquired beforehand from MRI or CT systems [19]. Such propagation velocity information will be used later in the real-time localization and tracking step.

However, calculating the length of $d_i$ and consequently the value of $k_i$ in Eq. (5) is challenging because the boundary surfaces of tissues are not mathematically determined. We need to compute $d_i$ as the length of a portion of the line-of-sight that is limited between two tissue boundary surfaces. To do that, we are seeking an effective algorithm to find the intersection points between each of the tissue boundary surfaces and the line-of-sight.

We propose to find the intersection points between boundary surfaces and the line-of-sight (passing through from emitter to the sensor) by solving the following minimization problem over all grid points on each boundary surface:

$$ I = \arg\min_p (L_1 + L_2) $$

(6)

where $I$ is the intersection point, $L_1$ is the length of the straight line from the sensor to the grid point $p$ and $L_2$ is the length of the line from grid point $p$ to the implant. As we see in Fig. 1, by minimizing the length $(L_1 + L_2)$ the multisegment line SPE converges to the straight line-of-sight SIE and this minimization occurs at the intersection point $I$.

After finding the intersection point that meets the minimization condition in Eq. (6) for each of the boundary surfaces, the length $d_i$,
can be obtained for each tissue layer as the distance between the two intersection points. After obtaining all $d_\delta$ for a specific path, we are able to calculate $v_{eq}$ for that path using Eq. (5).

Fig. 2 shows an example of tissue configuration consisting of three different tissue layers (fat, muscle and an organ tissue such as lung tissue) and their boundary surfaces among various tissue layers. In these figures, the top surface is the body skin, the middle surface is the boundary between muscle and fat and the bottom surface is the boundary between muscle and the organ tissue. The red points on the body skin are the sensors and the blue line is the line-of-sight from one of the sensors to the implant. $I_1$ and $I_2$ show the intersection points. Note that the sensors can be either mounted on the body skin, or can be installed in a fixed location beneath or above the patient’s body. The size of the sensor/antenna depends on the signal frequency that is used for localization [33]. The only thing that matters is that the location of the sensors should be known. In other words, the sensors can be placed in any arbitrary known position.

### 2.3. Problem formulation

In this section we present the problem formulation and show how we exploit the spatial sparsity to solve the location estimation problem. To clarify the formulations and distinguish the variables, we will use the lower-case italic bold letters to present a vector, upper-case italic bold letters to show a matrix and lower-case italic non-bold letters to present scalars.

Assume that each sensor collects $N_s$ signal samples at sampling frequency $F_s = 1/T_s$. Then we have

$$s_{\delta j} = c_\delta D_\delta s_\delta + n_\delta,$$  

where $s_\delta$ is the received signal by the $\delta$th sensor, $s_\delta$ is the vector of $N_s$ samples of the transmitted signal, $n_\delta$ is the noise vector, $c_\delta$ is the gain including path loss and a phase shift that can be written as $c_\delta = |\beta| e^{j\phi}$ where $\beta$ represents the real path loss, $\phi = -2\pi f_c r_\delta$ is constant phase, and $f_c$ is the carrier frequency. $D_\delta$ is the time sample shift operator by $m_\delta = (r_\delta/T_s)$, $r_\delta$ is the distance between sensor and the $\delta$th sensor and $v_{eq}$ is the equivalent velocity on the path from emitter to the $\delta$th sensor derived from (5). We can write $D_\delta = D_\delta^{n_\delta}$ where $D_\delta$ is an $N_s \times N_s$ permutation matrix defined as

$$[D_\delta]_{ij} = \begin{cases} 1 & \text{if } i = j + 1 \\ 1 & \text{if } i = 1, j = N_s \\ 0 & \text{otherwise} \end{cases}; \quad D_\delta = \begin{bmatrix} 0 & 1 & \cdots & 0 \\ 1 & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 1 \end{bmatrix}$$

Now, we assign a number $\delta_{x,y,z}$ to each one of the grid points $(x,y,z)$. Assume that $\delta_{x,y,z} = 1$ for the grid point containing the implant beacon and $\delta_{x,y,z} = 0$ for the rest of the grid points. Thus, by rephrasing Eq. (7), the signal vector received by $\delta$th sensor is given by

$$s_{\delta j} = \sum_{x,y,z} \sum_{\delta_{x,y,z}} \delta_{x,y,z} a_{x,y,z} D_{\delta j x,y,z} s_\delta + n_\delta,$$  

where $D_{\delta j x,y,z}$ is the time sample shift operator w.r.t. sensor $j$ assuming that the emitter is located in the grid point $(x,y,z)$ and the
summations are over all grid points in the desired (x,y,z) range. Note that \( \mathbf{D}_{x,y,z} \) and \( \alpha_{x,y,z} \) are known in Eq. (9) because the position of the sensor \( l \) and each grid point \( (x,y,z) \) is known and thus we are able to find the path loss and delay from Eqs. (2) and (5) for the path from grid points \( (x,y,z) \) to the sensor \( l \). The unknown term is \( \delta_{x,y,z} \) which represents whether a grid point contains the implant beacon or not. If we re-form all grid points into a column vector and re-arrange the indices, then we have

\[
\mathbf{s}_{i,j} = \sum_{n=1}^{N} \delta_{n} \alpha_{i,n} \mathbf{D}_{i,n} \mathbf{s}_{i} + \mathbf{n}_{i}
\]

where \( N \) is the total number of grid points. Now, we define the tall matrix \( \mathbf{T}_{\mathbf{n}} \) as the delay and path-loss operator with respect to all \( L \) sensors, assuming that the implant is located in grid point \( n \) (the received signal comes from the grid point \( n \)) as follows:

\[
\mathbf{T}_{\mathbf{n}} = \begin{bmatrix}
\alpha_{1,1} \mathbf{D}_{1,n} \\
\alpha_{2,1} \mathbf{D}_{2,n} \\
\vdots \\
\alpha_{\mathbf{n},1} \mathbf{D}_{\mathbf{n},n}
\end{bmatrix}
\]

where \( N_{L} \) is the number of signal samples.

Then, we define \( \mathbf{\theta}_{n} = \mathbf{s}_{n} \times \mathbf{s} \) as an \( L_{N} \times 1 \) vector including all signals received by all \( L \) sensors when the emitter is located at grid point \( n \) as

\[
\mathbf{\theta}_{n} = \mathbf{T}_{\mathbf{n}} \times \mathbf{\Theta}
\]

where \( \times \) is the regular matrix multiplication.

Now, we expand our results over all grid points by arranging all vectors \( \mathbf{\theta}_{n} \) for \( n=1, \ldots, N \) as the columns of a matrix \( \mathbf{\Theta} \) as

\[
\mathbf{\Theta} = \begin{bmatrix}
\mathbf{\theta}_{1} \\
\mathbf{\theta}_{2} \\
\vdots \\
\mathbf{\theta}_{N_{L} \times N_{L}}
\end{bmatrix}
\]

then we have

\[
\mathbf{s} = \mathbf{\Theta} \times \mathbf{v} + \mathbf{n}
\]

where \( \mathbf{s} = \begin{bmatrix} \mathbf{s}_{1}^T & \mathbf{s}_{2}^T & \ldots & \mathbf{s}_{L}^T \end{bmatrix}^T \) is the \( L_{N} \times 1 \) vector of all received signal samples by \( L \) sensors, \( \mathbf{v} = [\delta_{1}, \delta_{2}, \ldots, \delta_{n}]^T \) \( n_{L+1} \) is the sparse vector of \( \delta \)-values assigned to each grid point and \( \mathbf{n} \) is the vector of noise. Since each element of vector \( \mathbf{v} \) corresponds to a grid point in the grid space, we can estimate the location of the implant by extracting the position of non-zero elements of the sparsest vector \( \mathbf{v} \) that minimizes the cost (fit of solution to the observation) which is defined as the Euclidean distance between \( \mathbf{s}_{i} \) and \( \mathbf{\Theta} \times \mathbf{v} \).

Thus, we can solve our problem by forming the regularized Basis Pursuit Denoising (BPD or equivalently Lasso) problem as follows [22]:

\[
\mathbf{v} = \arg \min_{\mathbf{v}} \| \mathbf{v} \|_{1} + \lambda \| \mathbf{\Theta} \times \mathbf{v} - \mathbf{r} \|_{2}
\]

where \( \| \cdot \| \) is the \( \ell_{p} \)-norm defined as \( \| \mathbf{v} \| = \sqrt[2]{\sum_{i} |v_{i}|^{p}} \) and \( \lambda \) is the regularization parameter that adjusts the balance between cost (fit) and sparsity. Selecting a proper \( \lambda \) is important in regularization problems; by increasing the value of \( \lambda \), the penalty on cost gets higher and it leads to a good fit to the observation. However, if we select a too large regularization parameter, it may fail to achieve a sparse solution. Various methods have been proposed in the literature for automated \( \lambda \) selection (such as in [23]). However, it is usually possible to find reasonable choices for \( \lambda \) by empirical methods.

2.4. Reducing computational complexity for 3-dimensional localization

In this section we propose an alternative approach to reduce the computational complexity of the problem. This is very helpful in cases when we have a large number of grid points, such as implementing 3-dimensional high-resolution localization in a large area. In this method, we can split the area of interest into several sub-areas. We can form Eq.(15) for each sub-area and find the best grid point that meets the minimization problem. In a second step, we will only form the minimization problem among the selected grid points from each sub-area to find the final result. Note that the computational complexity of the minimization problem in Eq. (15) using traditional convex optimization methods for a vector \( \mathbf{v} \) of length \( N \) is about \( O(N^{3}) \). Thus, the computational complexity decreases significantly by reducing the size of the sparse vector.

Assume that we aim to estimate the implant position in a \( N_{x} \times N_{y} \times N_{z} \) grid space. Thus, the vector \( \mathbf{v} \) has \( N_{x}N_{y}N_{z} \) elements and the computational complexity of the minimization problem is \( O(n_{x}n_{y}n_{z}^{3}) \). Now, if we split the grid space into \( N_{z} \) grid planes with the size of \( N_{x} \times N_{y} \) each (as shown in Fig. 3), we will have the complexity of \( O(N_{x}N_{y}n_{z}^{3}) \) for each plane. Consequently, the total computational complexity will be \( O(n_{z}(N_{x}N_{y}n_{z}^{3})) \) for all \( N_{z} \) grid planes in addition to \( O(N_{z}^{2}) \) for final step. This is almost \( O(N_{z}^{2}) \) times smaller than the original problem.

Another method that can be applied to reduce the computational load is to start with a coarse grid, and then increase the resolution of the grid iteratively. In other words, after estimating the approximate location of the target in a coarse grid space, we generate a finer grid in a smaller area of interest around the approximately estimated position, and then re-calculate the location in this new area. We continue this process until we achieve the desired positioning accuracy.

3. Results

We have to note that the traditional TOA-based method usually fails to achieve accurate results for in-body localization unless employing ultra wide band (UWB) signals (which are not compliant to the Medical Implant Communication Services standards).

However, in our method, since the localization is based on all RSS, TOA and phase shift parameters, we can achieve accurate results. In the case of using narrowband signals, TOA information only helps to estimate a coarse approximation of the implant position. However, RSS and phase shift provide much more information about the emitter location and enable the system to find the accurate position of the implant. Again, we have to note that in the proposed method, we do not measure TOA or RSS or phase shift. Instead, we exploit the total location information that is provided by these parameters to estimate the position of the implant in one single stage.

We examined the performance of the proposed method using Monte-Carlo computer simulations with 100 runs for each position (a new random noise vector is generated for each run). In the first scenario, we used 16 sensors to estimate the location of the implant in a 3-dimensional space. The noise is zero-mean white Gaussian with SNR=20 dB. In this simulation, we also simulated the multipath condition (signal reflections from tissue boundaries) using reflector points at randomly chosen locations.
As described in Section 2.4, we started with a coarse grid of 10 x 10 x 5 cm³ with grid points spacing of 1 cm to find the approximate location, and then continue with finer grids in a smaller area of interest around the approximately estimated position. We used the ultimatum grid point spacing of 0.5 mm as the finest grid. The codes are implemented in MATLAB on a computer with a 2.6 GHz dual core CPU and 8 GB RAM. The localization process took about 7 s with 16 sensors, and about 2 s with 4 sensors. However, the MATLAB environment is not well-suited to real-time computing, and so a much shorter time would be achievable using a real-time computing environment.

Fig. 4(a) demonstrates the true position of the implant (in red) and the estimated position by the proposed method (in blue) using 16 sensors. Note that the position of the implant is not necessarily on the grid points. Fig. 4(b) shows the error in positioning defined as

\[ e = \sqrt{e_x^2 + e_y^2 + e_z^2} \]  

where \( e_x, e_y \) and \( e_z \) are RMS (root mean square) errors in positioning for \( X, Y \) and \( Z \) dimensions respectively. RMS error is defined as

\[ \text{RMSE}(x) = \sqrt{\frac{\sum_{i=1}^{N} (x_i - \bar{x})^2}{N}} \]

It is shown that the positioning error is less than 1.5 mm in the worst case.

In the second scenario, we examined the performance of the proposed method in the case when the body tissue configuration is not exactly known and there is uncertainty on the tissue configuration and tissue boundaries. We used Monte-Carlo computer simulations with 100 runs for each position (Again, the codes are implemented in MATLAB and new random noise vector is generated for each run). To emulate this uncertainty, we added unknown random noise matrices to the exactly determined tissue boundaries.

Fig. 5 shows the simulation results for the two cases. Fig. 5(a) shows a simple pattern for tumor (or implant) movement in \( X \) direction, (b) RMS error for implant location estimation for the movement pattern in (a) using 8 sensors in two cases: when the tissue boundary surfaces are perfectly known (red-square curve) and when there is some uncertainty about the boundary surfaces with unknown boundary points variation of 3 mm (blue-circle curve). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

It is worth highlighting that in this simulation a boundary variation level of 3 mm only increased the localization error by 0.5 mm. Note that the position of the implant is not necessarily on the grid points. In this case, the algorithm finds the nearest grid point to the implant location. Thus, a significant portion of the errors results from the distance between the implant and the determined nearest grid point close to it. This kind of error can be reduced by employing finer grids in the processing, which would of course increase the computational overhead accordingly.
signal power and bandwidth with regard to the protection of human health [32] also make it more challenging to achieve accurate location estimation. Given all aforementioned adverse factors, traditional in-body localization methods that explicitly estimate RSS or TOA are often inefficient and inaccurate.

In this paper, we developed a novel tissue-adaptive method by considering both the propagation velocity and path loss exponent as location-dependent parameters that can be exploited to estimate the implant location more precisely. Unlike the classic methods, we directly estimate the location of the implant without going through the intermediate stage of TOA or RSS estimations. This strategy leads to accurate results in a robust solution that can effectively deal with in-body multipath conditions.

5. Conclusion

Knowing the exact position of the tumor is a very critical prerequisite in radiation therapy. Since the position of the tumor changes because of the respiration, patient movements and other factors, a real-time tumor tracking technique is highly desirable during the radiation therapy in order to ensure to deliver a precise amount of radiation to the tumor region without damaging the surrounding healthy tissues. In this paper, we proposed an accurate tumor position estimation method that implicitly uses TOA, path loss, and phase shift parameters based on spatial sparsity in 3D space. We estimate the position of the target tumor by processing the received signals from only one implantable RF transmitter.

The performance of the proposed method was evaluated using various computer simulations under different scenarios. In these simulations, the location of the implant has been chosen randomly, the received signals were noisy with additive white Gaussian noise, and the multipath condition has been simulated using randomly chosen reflector points. The results show that the proposed method is very accurate in location estimation, even when we use a small number of sensors (only 4 sensors), a small number of signal samples (only 64 signal samples), and even when a level of uncertainty of the tissue configuration and boundaries exist.

Conflict of interest statement

The authors of this manuscript have no conflicts of interest.

References


