MAPPING OF ENCLOSED BUILDINGS USING MOBILE RADIO TOMOGRAPHY

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KEYWORDS

Mobile radio tomography, convex optimization, regularization, simulation, robotics.

ABSTRACT

In this paper we consider the task of inner objects mapping for the building with a bunch of moving around it autonomous agents which use narrow beam of radio waves using WiFi frequency (2.4 GHz). Linear model of pixel-wise radio waves attenuation is considered. SIRT algorithm with TV and Tikhonov regularizations is used for the task of tomography reconstruction. Properties of the presented model are studied during simulation using synthetic data consisting of 8 buildings with inner object with different shapes. Dependency between mapping quality and transmission power is found. Simulation results confirm suggested approachs usability.

INTRODUCTION

In real life there are situations when military and special services need to determine positions of objects and people inside the building without possibility of entering. We would like to solve this problem with a bunch of mobile transmitters and receivers which locate around the building and send signals through it to each other. Method needs to be adequately protective of human health and the environment at the same time, therefore we cannot use the excessively hard and powerful radiation. The result of sounding and reconstruction of the building is a two-dimensional map of items locations (walls, objects, people) inside it, so this task is called the mapping an inaccessible building. Since the height of sounding sensors is fixed the resulting map is two-dimensional.

It is necessary to use a signal capable of passing through objects and spreading over long distances to build a solution of this problem. Methods based on radio waves are suitable for the task because it is important not to cause harm to environment and people. The narrow beam of high-frequency radio waves is preferable to use, since they do not slide around obstacles but travel through them being partially absorbed and reflected. This property of radio waves can be used for determining the characteristics of obstacles.

The most studied method of mapping is based on ground-penetrating radar. It uses principles of active radar properties, i.e. measurement of parameters (delay, phase, etc.) of the signal that is reflected from observed object. There are commercial systems based on this approach: PulsON (Time Domain Corporation 2016), ImpSAR (Eureka Aerospace 2009). An example of such systems is the ThruMapper (Tan et al. 2017). The ThruMapper system is a mobile platform which moves along the main corridor of the building and maps the building without entering rooms. The main disadvantage of this method is the exponential growth of the required signals power with increase in the thickness of walls and other charted objects.

Another group of methods for mapping is based on inverse tomography task. Diffraction and transmission radio tomography is used to solve the problem of mapping when it is possible to make a set of soundings from various positions around the building. Diffraction radio tomography is based on measurements of reflected electromagnetic waves parameters. Simulated experiments of diffraction tomography are presented in (Bardak and Saed 2014), possibility of mapping real data

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is shown in (Sukhanov et al. 2015). Diffraction radio tomography requires to collect projection data frequently, which makes the method inapplicable in real conditions, despite the high detail of the information on the resulting maps. Also diffraction radio tomography has same problem as ground-penetrating radars (the exponential growth of the required signals power with increase in the thickness of walls and objects).

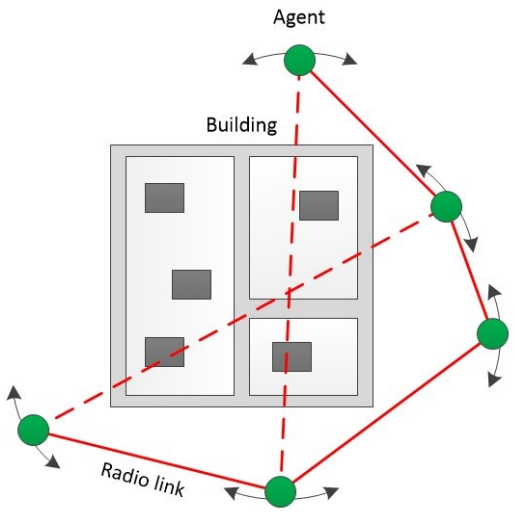
Radio tomography methods are based on absorption of radiation are divided into radio tomography and mobile radio tomography. In the radio tomography method network of stationary transceivers located around the observable area is used. With these transceivers the projection data is collected and then the inverse tomography problem is solved (Wilson and Patwari. 2010, Wilson and Patwari. 2011). The main disadvantage of this method is a fixed number of transceivers, which must be set up at pre-defined positions at the beginning of the measurements. Method of mobile radio tomography lacks this disadvantage, since it uses a network of mobile transceivers that allows to adjust the coverage of the observed zone if necessary (Van der Meij 2016, Helwerda 2016, Batenburg et al 2016). The usage of a mobile platform for radio tomography brings new challenges. For example, one needs to create the route of travel for transceivers, maintain precise positioning between them and keep the channel of data transfer up. However, method of mobile tomography makes it possible to obtain much more projection data, which makes it perspective for more accurate mapping of inaccessible building.

It would be feasible to use autonomous unmanned mobile tomographic robots, i.e. wheeled robots, if we considered the distinctive features of practical application (for special and military operations). At least two (transmitter and receiver) mobile agents for the purposes of transmission radio tomography must be used. It is better to use several pairs of mobile devices simultaneously for faster mapping which are capable to continue work even when a part of them is out of order. So, we are talking about a group of robots without centralized control, that perform remote mapping of inaccessible building together. The collaborative behaviour of a similar robots group for mapping the open area was considered in work (Shvets et al. 2015). Since the interaction of a group of mobile agents in practice is performed through WiFi (frequency 2.4GHz), it seems reasonable to choose this frequency for sounding, although we can use any other waves frequency of the microwave band that can travel through obstacles.

A distinctive feature of the application of mobile radio tomography to the considered task (especially using a group without centralized control) is non-fixed step of the sounding, which makes it impossible to use integral algorithms to find solution of the tomography problem. So we shall use algebraic methods then (Buzmakov et al. 2017, Ingacheva et al. 2017). A similar approach based on applying algebraic methods for mapping rooms with sonars is proposed in paper (Shvets et al. 2014). In this work the linear equations systems of large dimension are solved by continuous optimization methods.

SIMULATION MODEL

The model of mobile radio tomography we used in our experiments is shown in fig.1. It includes several mobile unmanned agents (tomography set-ups) which can emit and receive radio signals. They move around the building collecting projection data in certain positions and record the signal that has been partially attenuated along given direction (dashed line in Fig. 1). Solution of the inverse radio tomography problem can be found based on the collected projection data. The accuracy of resulting map of the building directly depends on the number of projections.



Figures 1: Radio tomography model.

It is necessary to accurately set the receiver and the transmitter, since it is required to know exact positions of both agents to solve inverse radio tomography problem. We consider that agents interact with each other using WiFi frequency (straight lines in Fig. 1) which is also used for sounding building.

Radio signal formation

For evaluation of received by agent radio signal power we use linear model of attenuation (Wilson and Patwari, 2010). This model relies only on dielectric properties of the objects the signal passes, but not considering the angle between the radio wave and object. Using this model, we can split entire mapping space into a separate pixels and work with them independently.

We can present power of registered signal P(l) for radio wave l as difference between the transmitted power P_t and summation of the losses in every pixel L(l), the losses of radio signal propagation L_m and noise η:

$$P(l) = P_t - L(l) - L_m - \eta \,. \qquad (1)$$

The losses of radio waves propagation L_m depend on the emitted signal power, coefficients of signal empowerment of transmitter, receiver and the distance between them. This distance is constant in our simulation model, thereby it is equal to the size of mapping space N. Total loss of radio wave can be written as a loss in every pixel multiplied by weight of the corresponding pixel:

$$L(l) = \sum_{i,j=1}^{N} w_{ij}(l) L_{ij}, \quad (2)$$

where $w_{ij}(l)$ is weight of pixel in coordinate (i, j) for radio wave l, L_{ij} is loss in corresponding pixel.
We can separate loss of radio wave into 2 types: loss during pass through dielectric materials and loss during pass of free space:

$$L_{ij} = \begin{cases} Lv_{ij}, & (i,j) \in Object; \\ 0, & otherwise. \end{cases} \quad (3)$$

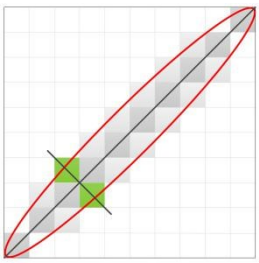
Loss in dielectric material can be written as:

$$Lv_{ij} = 10\lg(Pn_{ij}) - 10\lg(P_v(\Delta d)_{ij}), \quad (4)$$

where Pn_{ij} is radio wave power which crosses the border between different objects with different resistances in pixel (i, j), $P_v(\Delta d)_{ij}$ is radio wave power after pass through dielectric material of thickness Δd (in our case Δd is the size of a pixel and it equals 10 cm). Thereby loss during pass through pixel (i, j), can be calculated as:

$$P_v(\Delta d)_{ij} = (Pn_{ij} - Pr_{ij}) A(\Delta d), \quad (5)$$

where Pr_{ij} is reflected part of the power, $A(\Delta d)$ – attenuation coefficient according to the interference with environment, which depends on Δd exponentially.
We use ellipsoidal model to determine weight of a pixel. Every matrix of weights defines only one radio wave. If we know positions of emitter and receiver we can describe every radio wave with this matrix. For example, on fig 2. we can see a matrix for a wave within ellipsoidal model.



Figures 2: Method of calculating radio wave weight.

This matrix can be also written as equation:

$$w_i = \begin{cases} \frac{1}{n}, i \in link; \\ 0, otherwise. \end{cases} \quad (5)$$

Where n is the number of pixels along the smallest eigenvector of the ellipse (green squares in Fig.2). Ellipsoidal model describes real life case better than a straight-line radio wave model since the wave forms an ellipsoid of revolution (spheroid) during propagation called Fresnel zone.

TOMOGRAPHIC RECONSTRUCTION

We consider the problem of mobile radio tomography as a system of linear equations

$$Wx = p. \quad (6)$$

where W is weight matrix in which the line corresponds to a radio wave, x is a column vector of an unknown region function of $N \times N$ pixels, p is a column vector of the obtained projection data. A solution of the system (6) is found using one of iterative algorithms of nonlinear optimization (Nocedal and Wright 1999). The standard way to solve system (6) is to minimize the follow expression:

$$\|Wx - p\|_2^2 \to \min_x. \quad (7)$$

The advantage of algebraic methods is its adaptability the particular task. For example, a priori knowledge about reconstruction function can be included in system (6). One way to modify the algorithm is to add a problem-specific regularization term.
TV-regularization (Total variation regularization) and Tikhonov regularization is used in this paper. TV-regularization provide the smoothness of an unknown function, so the minimal difference between neighbouring pixels should be achieved. Penalty for large value of functions gradient is imposed as ($\|\nabla x\|$) (Estrela et al. 2016). Tikhonov regularization is necessary to ensure that there will be no extremely large values in the unknown function. Penalty for L2 norm of unknown function is imposed as ($\|x\|^2$) (Gockenbach 2016). The final equation of the minimized functional with both regularizations can be written as:

$$\|Wx - p\|_2^2 + \alpha\|x\|_2^2 + \beta\|\nabla x\|_1 \to \min_x . \quad (8)$$

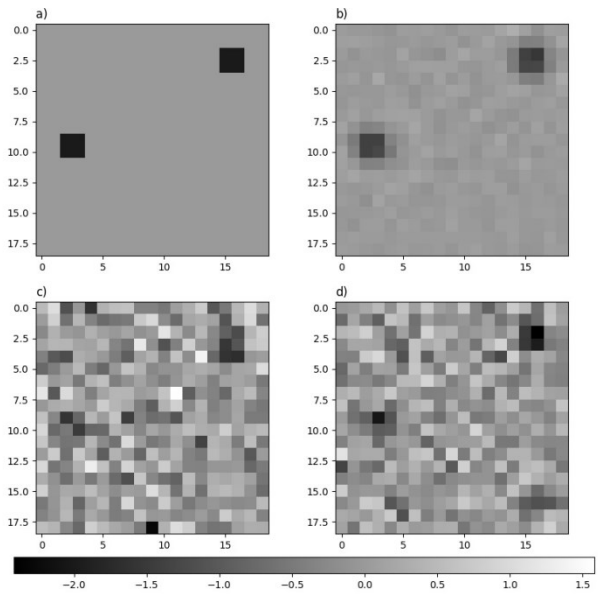
The numbers α and β are the configurable parameters of the algorithm. The steepest gradient method was chosen for minimization the functional (8).

NOISE MODEL

To add noise in our model we use the results of the research described in the paper (Ganesh and Pahlavan 1990). Author of this paper studied the approximation of noise distribution in the propagation of radio waves in buildings. They approximated the noise for radio wave by the log-normal distribution $lnN(\mu, \sigma)$, with mathematical expectation $\mu = 0$.
Since we use power in decibels in our model, we need to use a normal distribution.

COMPARISION WITH REAL DATA

To validate our simulation algorithm, we performed comparison of results from suggested approach with real data from paper (Batenburg et al 2016). In this work Dutch scientists performed a set of experiments with people in the building room without any obstacles. One of their experiment is illustrated in Fig. 3 a). The black squares in the image correspond to people, grey colour represents open area. The size of the grid 19x19 pixels, where one pixel is 16.75 cm2 square area. Using this simulation, we have calculated projection data with the same configuration of agents. Then we have select noise parameters and reconstruct obtained projection data with 100 iterations. The selected standart deviation $\sigma = 6.3$. We have not added any regularization to save real problem-specific noise in reconstructions. Examples of reconstruction data taken from the real experiment and our simulation using ellipsoidal weights models are shown in fig. 3.



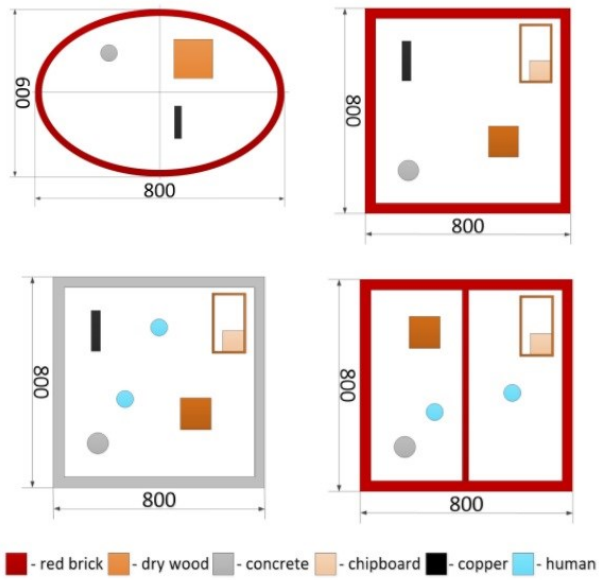
Figures 3: Real data comparison: a) model object, b) simulation data without noise reconstruction, c) real data reconstruction, d) simulation data with noise reconstruction.

To evaluate the quality or the similarity of experiment and simulation projection data we calculate mean square error (MSE). The MSE between real data and simulation without noise is 0.029, when for our noisy and not noisy data MSE is 0.024. From this comparison it is obvious that elliptical model with Fresnel zones and Log-normal noise distribution describes well conditions of real experiments enough.

EXPERIMENTAL SETUP

Dataset

For our synthetic data we have used five common materials in building: bricks, concrete, wood, chipboard and copper (any metal reflecting radio waves can be used). In some cases, we have added model of human body. Using these materials, we have created a dataset with 8 objects for studying possible applications of radio tomography methods in task of mapping enclosed buildings. Several images of objects from our dataset are shown in fig.4.



Figures 4: Examples of images from our dataset.

Mapping quality estimation

For quality measurement of reconstructed space, we calculated total error for every object from dataset using distance in L2 norm divided by N^2 - total number of pixels in target space:

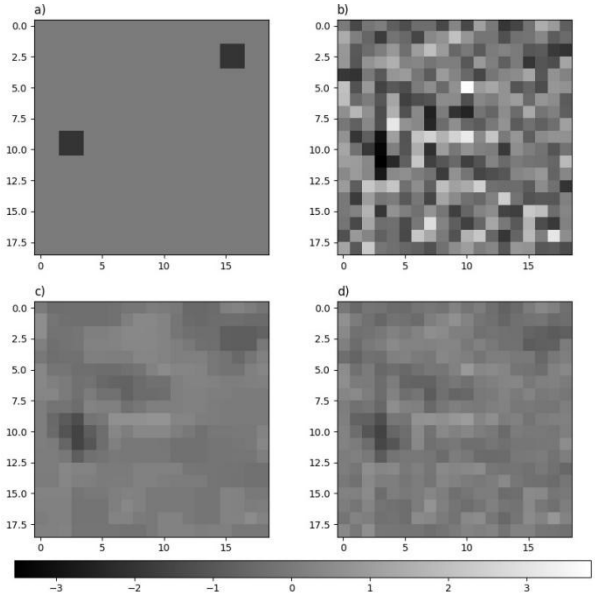
$$E = \sum_{z=1}^{8} \sum_{i,j} (M_{ij}^{z} - R_{ij}^{z})^2 \Big/ N^2 , \qquad (9)$$

where z is object number, M_{ij}^{z} is a pixel from synthetic object, R_{ij}^{z} is reconstructed pixel. Size of both simulated and reconstructed spaces is $\{N \times N\}$.

EXPERIMENTAL RESULT

According to the comparison of results against real data, it can be seen that existing WiFi devices for home usage are not suitable for mapping inaccessible buildings. The result of reconstruction is noisy and it is not possible to separate standalone objects from the background.

However, hardware-based and software-based approaches can be applied for noise reduction. The software approach is based on a modified spatial reconstruction algorithm, with addition of Tikhonov regularization and TV-regularization as noise suppressors. The experimental results show that Tikhonov regularization does not improve the quality of reconstructed map, because the noise in the projection data does not contain any sticking out values. The reconstruction results with different type of regularization are shown in Fig. 5. One can see structural similarity and different loss level in Fig. 5b) and Fig. 5d).



Figures 5: Reconstruction with different regularization type: a) model object, b) without regularization, c) TV regularization, d) Tikhonov regularization.

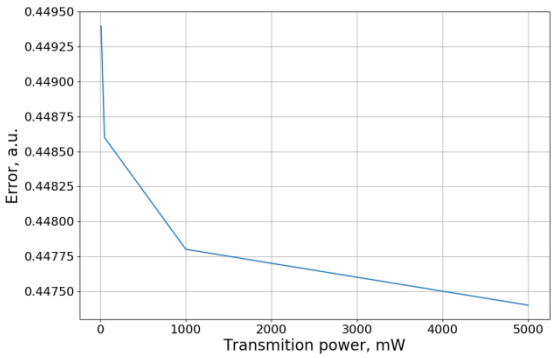
On the contrary, TV-regularization suppresses smoothly distributed noise very well (Fig. 5c)). We chose the regularization parameter for the visual noise on reconstruction to be as low as possible, while keeping the boundaries of objects visually distinguishable. Thus, for the dataset represented before (see Fig. 4) we took the parameter for TV-regularization equal to 5 and the parameter for Tikhonov regularization is 0.

The hardware approach of noise suppression is based on tuning the properties of receivers and transmitters. We have conducted experiments to demonstrate how increase in the transmitter power affects the reconstruction quality. For all model objects from our dataset we have calculated the projection data at 60 uniformly distributed rotation angles, the spatial step on each angle position has been chosen as minimal as possible (in each pixel). The reconstruction of projection data was done with 100 iterations in each experiment. Total error has been calculated by equation (9). The results of the experiment are shown in Table 1.

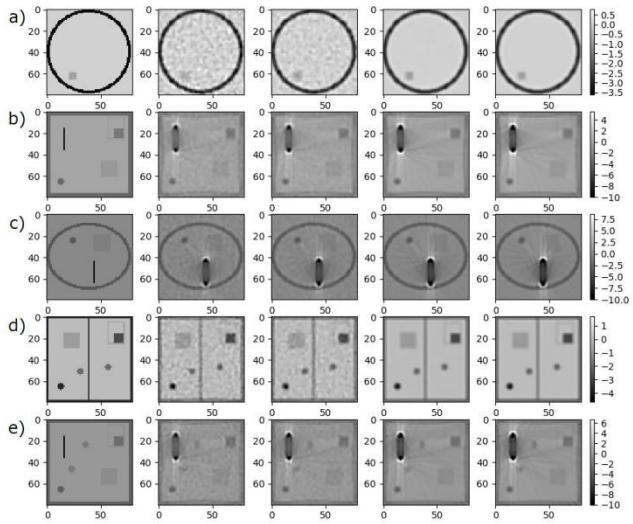
Table 1: Reconstruction and total error with different transmission power.

Object number \ Power	10 mW	50 mW	1W	5 W
1	0.0192	0.0147	0.0128	0.0122
2	0.0058	0.0056	0.0053	0.0052
3	0.7119	0.7114	0.7106	0.7102
4	0.7128	0.7124	0.7116	0.7112
5	0.7123	0.7119	0.7112	0.7108
6	0,7125	0,7122	0,7114	0,7110
7	0,0087	0,0085	0,0080	0,0078
8	0,7123	0,7119	0,7112	0,7109
Total	0,4494	0,4486	0,4478	0,4474

The curve of the dependence between reconstructed building map quality and the transmitter power is shown in Fig 6. Reconstructions of five model objects are shown in Fig. 7. Dependency between mapping quality and initial power is very similar for different values of regularization parameters in reconstruction algorithm.



Figures 6: Dependencies between initial power and reconstruction quality.



Figures 7: Different levels of power. Each line represents the same model object with different initial power.

One can see from the experimental graph that the quality of the mapped area is almost exponentially proportional to the power of the transmitter. It should be also noted that the quality of the reconstructed map is lower than building contains metal parts. The close objects to copper part are not selected on map (Fig. 7 b, c, e). Thus, the proposed radio tomographic algorithm is well suited for mapping of buildings that does not have metal elements.

CONCLUSION

In this paper we have demonstrated radio tomography technique usage possibility in the task of mapping enclosed buildings using simulated experiments. After the absorption model simulation accuracy of radio waves was compared with results from work (Batenburg et al 2016). The data acquirement process was considered as a set of consecutive steps, i.e. signals interference from different simultaneous projections was not counted. Therefore, there is also an interesting problem about possibility of receiving signals from more than one agents at the same time for faster mapping that was not consider in this paper.

Dependencies representing the reconstruction quality as a function of signal strength of the transmitter was obtained. The results of the experiment show that applying method of mobile radio tomography is well suited for mapping inaccessible building without metal items in their construction.

Experimental results also show that suggested approach is usable to map buildings in real life. Accuracy of inner objects map reconstruction is sufficient for usage in military or civilian operations.

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