Localization-assisted indoor acoustical data monitoring

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Summary
Monitoring of acoustical data is often done at fixed measurement stations to verify the compliance with environmental noise or work safety regulations. In this work, a different method is explored for monitoring acoustical conditions in indoor environments with the assistance of location information. Such method exploits a wideband localization system to determine the listener position with high accuracy, which serve, together with prior knowledge of the sound field, to assess the behaviour of the local acoustical data in the indoor environment. An application of this method is developed for the case study of a long partitioned virtual room, in which an ultra-wideband (UWB) localization system is used and the subject moves along a trajectory characterized by abrupt acoustical changes. First, the behaviour of various acoustical metrics is assessed along the trajectory. Then, the perspectives of this monitoring method are outlined and discussed.

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1. Introduction

The monitoring of acoustics data indoor is usually done with the aim of controlling the compliance of the overall noise exposition (e.g. noise dose) of workers with safety regulations [1]. Within this practice the static positions of the receiver are considered, as for instance are those in front or close to noisy machineries, but the real path of the receiver moving in the noisy space is not known. Another means of collecting sound, but with the movement of the receiver, is termed "sound walks". This research practice, which is common in the framework of soundscape studies [2], consists in the documentation of sound inputs outdoors in order to evaluate the quality of the listening sensations. Sound walks have a non-continuous logging of positions with precision typical of the global positioning system (GPS). But in cluttered environments (e.g., inside buildings, in urban canyons, and under tree canopies), the GPS performance is often degraded due to propagation impairments such as multipath and line-of-sight (LOS) blockage. These impairments present significant challenges to the design and operation of indoor tracking systems [3]. In fact the tracking process aims at determining the unknown position of mobile nodes (agents) based on measurements with respect to nodes in known positions (anchors) as well as others agents [4]. It typically occurs in two phases: a measurement phase in which agents make intra- and/or internode measurements using different sensors; and a location update phase, during which agents infer their positions based on prior knowledge and new measurements. Multipath resolvability in indoor environments of UWB signals [5]–[8] makes ultra-wideband (UWB)-TOA based technique ideal for high accuracy ranging in cluttered environments [9]–[11]. Bayesian filtering, based on mobility and perception models (also known as measurement models), can efficiently combine measurements from multiple sensors. In particular, both mobility and perception models affect the tracking performance and need to be carefully characterized [12]. Given an underlying technology, the localization and navigation performance also depends on the algorithm used [13]–[17]. Thanks to the UWB efficiency in indoor localization, the joint monitoring of position and sound, the latter in the form of acoustical parameters, the previous sound monitoring needs would be greatly improved. For instance it would be possible to better prevent excess exposition, for instance by informing the

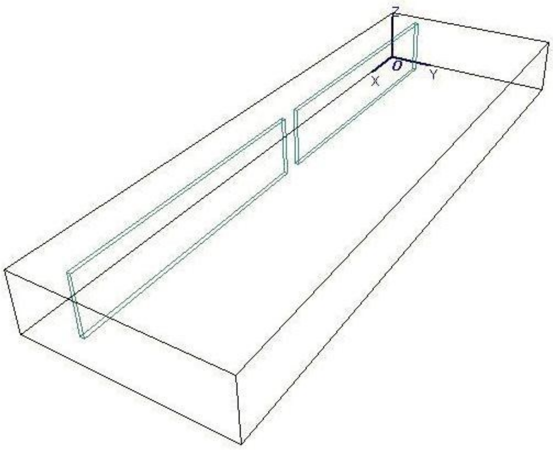

Figure 1: 3D sketch of the room.

receiver on the occurrence of too noisy or acoustically critical tracks (presence of harmful impulsive noise, excess of low frequencies etc..). Besides application in the public health sector, the dynamic tracking of position and sound could be a relevant asset in the control of environmental acoustics. In fact the knowledge of the sound paths would be needed in order to shape and adapt the sound field to the presence and to the needs of the receivers. In particular the conditioning of the sound field and its monitoring at the receiver could work as an active feedback system to reach the targets desired by the receiver depending on his/her activity. The present paper will focus on a preliminary case study exploring the above concepts and consisting in the simulation of sound tracks indoor in an acoustically difficult space, where sound conditions vary greatly and the listener experience is expected to change too. By simulating both the acoustical behavior and the localization along given tracks the performance of the method will be tested and compared with the acoustical just noticeable differences.

2. System model

The space used as case study is a rectangular room with dimensions 30m x 10m x 3m. The volume is subdivided by a 0.2m thin wall into two long corridors, whose widths are 2m and 8m respectively. The wall has three 1m openings equally spaced at extremes and in the middle so that the sub-partitions are 13.5m long (Fig. 1).
The materials at the boundaries are mostly sound absorbing: moquette on the floor, acoustic plaster on the lateral walls and on the partitioning wall, and an acoustic ceiling. The sound scattering of those flat surfaces was set to the minimal value of 0.05, and the transparency was set to zero. Two reference paths were defined, one short and one long which will be called “true” in the following. The short one includes 200 points spaced 8 cm apart with location number 1 closer to the origin in the narrower corridor (Fig. 2). After moving along the corridor the path turns with a 1m radius curve passing the opening in the middle and then turning back. Since the radio localization is not sensitive to height the receivers were all set at 1 m above the floor and the same height was given to the paths estimated below. The long path is composed of 380 locations and is similar to the previous one, but turns at the opening opposite to the start. For the acoustics simulations an omnidirectional source was placed in the corner opposite the origin at height 1.5 m and the conventional sound power of 31dB was given in order to have strength G values as sound level outputs. The commercial software Odeon 12.0 ® [18] was used for acoustic simulation with 10000 rays in multi-point response mode. The calculated parameters are the following

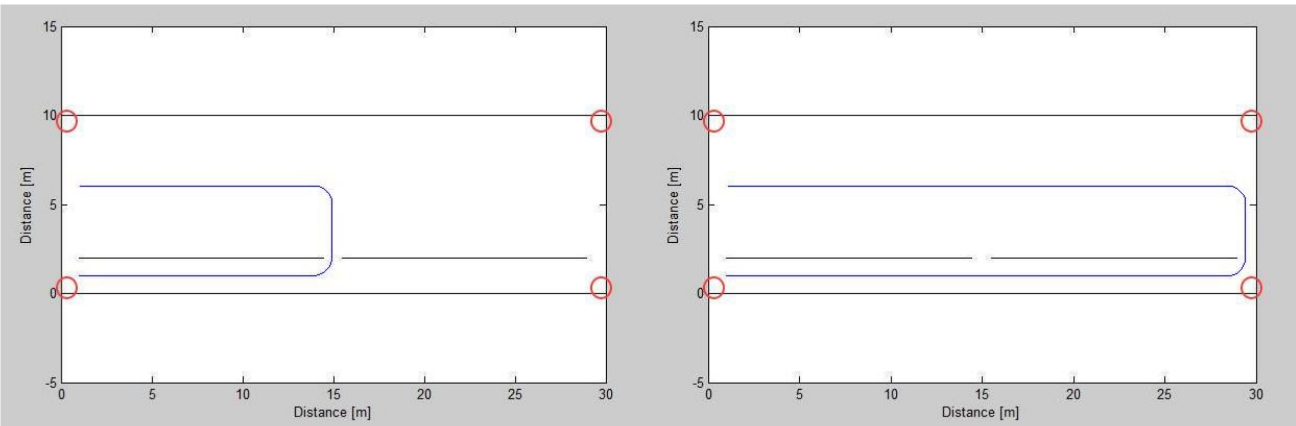

Figure 2: Plan view of the two “true” paths: short on the left and long on the right. The red circles indicate the locations of the radio antennas.

[19]: EDT_{Mid} (frequency average of 500Hz, 1kHz and 2 kHz octave bands), $T20_{Mid}$, $C50_{Mid}$, G (A-weighted) and STI [20]. The respective just noticeable differences were also considered as respectively: EDT: ± 5%;T_{20}: ± 7%;C_{50}: ± 1dB;G(A): ± 1dB;STI: ± 0.05. Firstly the "true" paths were simulated and then, with the same settings, the paths obtained by means of radio estimate of positions were processed to extract the respective acoustic parameters.

Anchors were placed at the four corners of the room and agents corresponded to the receivers locations Wireless propagation and ranging errors are modeled based on geometric visibility. In particular, for a given anchor, the agent is assumed undetected when it is in non-line-of-sight (NLOS) condition with respect to the anchor (i.e., another object obstruct the anchor-agent signal path) or detected when it is in line-of-sight (LOS) condition. If the agent is detected, we assume a TOA estimation error uniformly distributed in $[-1, 1]$ ns.

3. Bayesian tracking of positions

A tracking system can be modeled as a dynamical system, whose evolving state can include position, velocity, acceleration, and orientation [14]. The aim of a tracking system is to estimate the agent state $\mathbf{x}(t)$ at time t from multiple observations and prior knowledge. The observations are collected in discrete times $\{t_k\}$ with interval $\Delta_\mathrm{T} = t_k - t_{k-1}$ for all $k = 1,2,\ldots,K$, hence the agent state is updated every Δ_T seconds. We use the notation $\mathbf{x}_k = \mathbf{x}(t_k)$ and denote $\mathbf{z}_k = [z_{k,1}, z_{k,2}, \ldots, z_{k,N_k}]$ as the set of N_k observations at time t_k. The Bayesian filters estimate a probability density function (PDF) $b(\mathbf{x}_k)$ of $\mathbf{x}_k$, called belief, over the state space conditioned on all collected observations $\mathbf{z}_{1:k}$ until the time t_k:

$$b(\mathbf{x}_k) = f(\mathbf{x}_k|\mathbf{z}_{1:k}). \qquad (4)$$

The state $\mathbf{x}_k$ based on observations $\mathbf{z}_{1:k}$ can be estimated from (4) via maximum a posteriori estimation (MAP). Given the belief $b(\mathbf{x}_{k-1}) = f(\mathbf{x}_{k-1}|\mathbf{z}_{1:k-1})$ at time t_{k-1}, the *predicted* belief at time t_k is given by

$$b^-(\mathbf{x}_k) = f(\mathbf{x}_k|\mathbf{z}_{1:k-1}) = \int f_m(\mathbf{x}_k|\mathbf{x}_{k-1}) b(\mathbf{x}_{k-1})\, d\mathbf{x}_{k-1} \qquad (5)$$

where the term $f_m(\mathbf{x}_k|\mathbf{x}_{k-1})$ is the *mobility model* of the agent. The mobility model gives the PDF of current position $\mathbf{x}_k$ given the previous position $\mathbf{x}_{k-1}$, and it is related to the environment and the mobility behavior of the agent. When a new set of measurements is collected, the *updated* belief is given via Bayes' rule

$$b(\mathbf{x}_k) = \eta f_\mathrm{p}(\mathbf{z}_k|\mathbf{x}_k) b^-(\mathbf{x}_k)$$

where $\eta = 1/f(\mathbf{z}_k|\mathbf{z}_{1:k-1})$ and the term $f_\mathrm{p}(\mathbf{z}_k|\mathbf{x}_k)$ is the *perception model* of the agent. The perception model gives the PDF of observations $\mathbf{z}_k$ given the position $\mathbf{x}_k$ and is related to the environment and sensor technology. Bayesian filters differ in the representation of the PDF for each state $\mathbf{x}_k$. Among several implementations, those based on particle filters (PFs) provide a good compromise in terms of complexity, flexibility and accuracy [3]. Here, we consider belief computation via PFs, which is based on a sampling procedure known as sequential importance sampling (SIS) [21] with mobility and prediction models according to [12]. In particular, the mobility model with speed learning is adopted. Here, the tracking algorithm is based on particle filter (PF) with a number of particles N_par = 100, $\sigma^2_{m,k} = 1\, m^2$ for all k, and a value of $\sigma^2_{m,k}$ chosen such that the nth estimated particle at time k is within a circle centered at $\hat{\boldsymbol{\mu}}_n^{(k)}$ of radius $|\hat{\mathbf{v}}_k| T_L$, where $\hat{\mathbf{v}}_k$ is the estimated velocity at time t_k. Localization results are obtained considering an update rate $R_\mathrm{u} = 5$.

4. Acoustic performance

After the gathering of 20 "UWB estimated" short and long paths the respective acoustic parameters have been calculated and analyzed by simple average and standard deviations over the ensemble of paths. In the short paths the way the curved segment is estimated is critical, since the radio estimated points go across the wall and this implies an abrupt change of acoustics from one side to the other around point 120. Also the position estimates are more spread in this area, with a peak in correspondence of the bend. In the segment from start to curve the standard deviations of acoustic indicators are increasing since the points get more and more far from antennas with less accurate position estimate and in particular, from the acoustic point of view, the effect of the opening is also that of providing an uneven sound distribution in the narrower corridor especially close to the opening itself. After the turning point the localization is optimized and the acoustical data show only minimal deviations when passing through the wider corridor. In the long path the deviations of positions are smaller in general and the curve is correctly estimated. The area corresponding to the aperture at half of the narrow corridor is relatively the more critical both for localization and for dispersion of acoustic parameters. This is expected since this zone is most remote from antennas and the most critical for acoustic propagation. It is to be noted that the segment enclosed between the middle and the last aperture still shows some variability, which is anyway less than observed in the first segment of the same path. As discussed above for the short track, points in the wider corridor show only minimal deviations and are very consistent from position to position. Lastly it is also to be outlined that parameters are not equally affected by the data dispersion. In particular, while C50, EDT, T20 and partly G(A) show remarkable excursion in short and long paths, STI data seem much more stable.

5. Perceivable differences

At last the audibility of the discrepancies in the acoustic parameters between average radio estimated paths and the true ones was considered. The comparison is done by adding to the true values a strip corresponding to the respective just noticeable differences. Thus, when the radio estimated path results are out of the strip they are supposed to refer to different listening experiences. The analysis of the short path (Fig. 3) reflects the critical conditions at the curve in the middle, close to the opening. In fact the first path segment (points 0 – 90) displays unavoidable variability which is hardly audible, whereas when locations are closer to the opening deviations are much larger. Actually, data are such that they refer to two separate listening conditions, the former is in the narrow corridor and the latter in the wider one. From positions 90 to 130 this is evident for all parameters with a little more stable behavior of T20. Compared to the narrow corridor in fact, sound in the wider corridor is louder, more clear, a less reverberant (EDT) and speech there is more intelligible. Coming to the long paths (Fig. 4), the segment from position 90 to 110, that is passing by the opening in the straight line, one finds that C_{50},

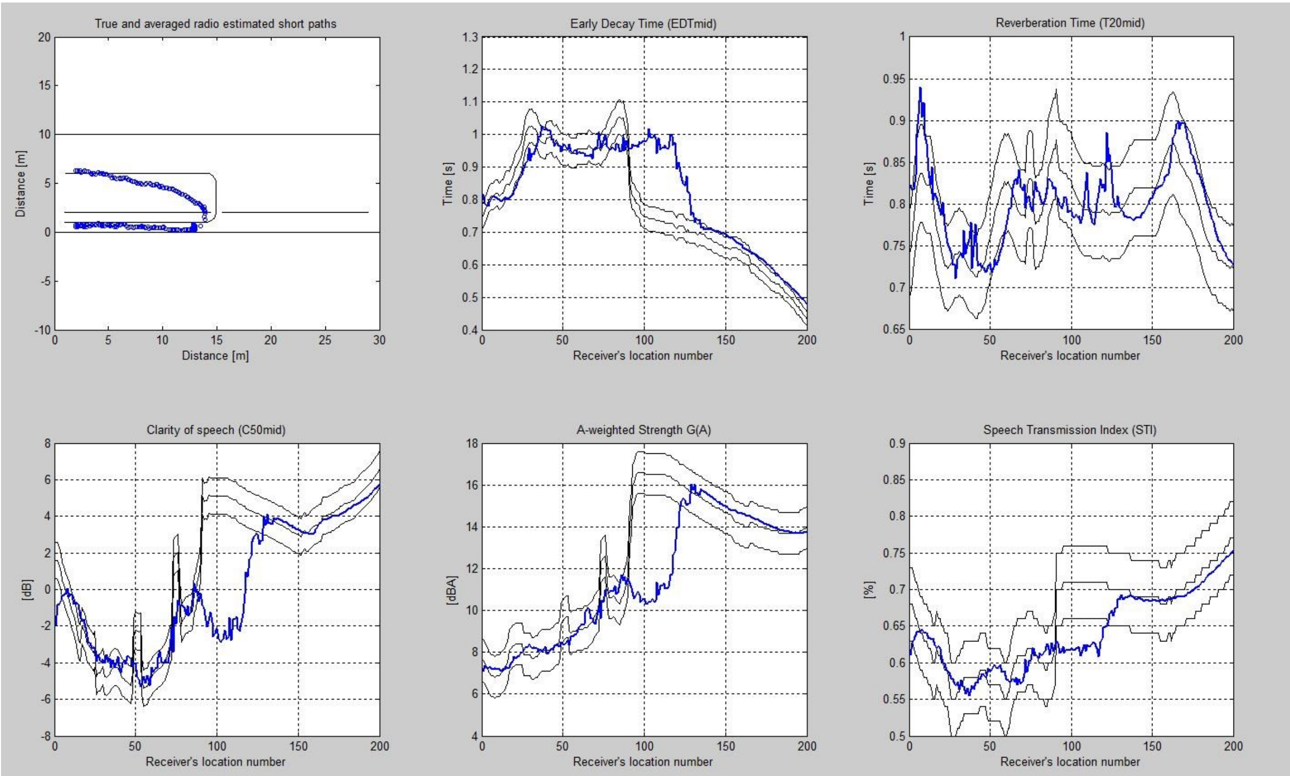

Figure 3: Average of radio estimated short paths with results from the true ones. The jnd of the acoustical parameters is also included in the plots for evaluation.

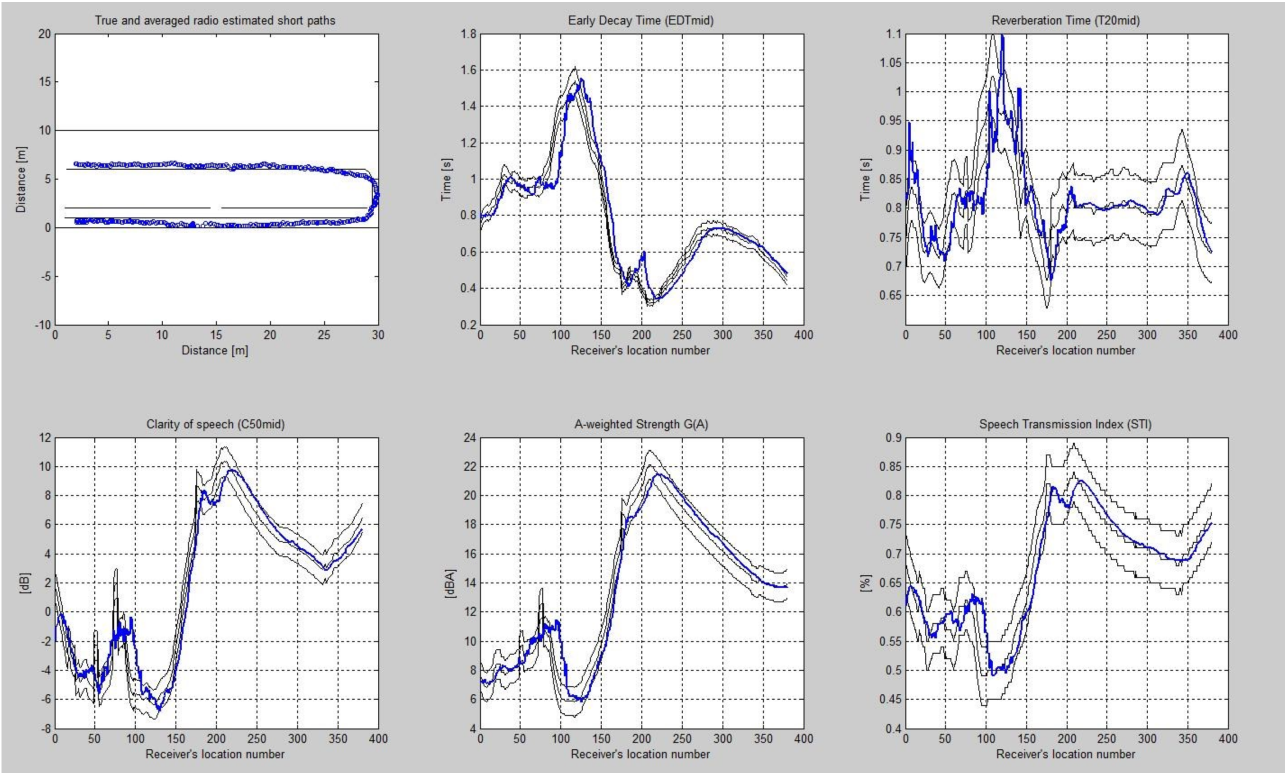

Figure 4: Same as Fig. 3 for the long paths.

G(A) and STI are overestimated whereas EDT and T20 are underestimated. A few local deviations are found in the curve (mainly in the intervals 183 - 187 for EDT and 192 – 215 for C50 and STI), but the global trend is generally respected with minor discrepancies between true and radio paths. When passing through the wider corridor the match of the two data sets is quite good and differences in the listening conditions should not be perceivable.

6. Concluding remarks

In this work the application of UWB to indoor acoustic monitoring was explored. Interesting findings were achieved as regards the most critical zones: for the short path the bend placed halfway, for the long path the area passing by the central opening and, in the second place, the bend close to the wall. From this it is found that the performance of the localization is especially sensitive to the geometrical peculiarities of the space and thus a strategy of improvement could be to relocate or add antennas close to the openings. Such opening are in fact often critical from the acoustic point of view, since they are usually characterized by a leap in the acoustic parameters. Furthermore, an improved localization from the beginning of the path would decrease significantly the lag of estimated points with respect to the true path and hence gain a significant accuracy in the calculation of the acoustic parameters.

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