Anchor placement in indoor object tracking systems for virtual reality simulations

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ABSTRACT

Indoor Object Tracking Systems (IOTS) allow sensing moving objects inside a closed space, where GPS is not available. Besides the most popular use, indoor navigation, IOTS may also contribute to extend the operational range and the possible applications of Virtual Reality (VR) and Augmented Reality (AR) based technologies, such as complex training scenarios or entertainment oriented simulations: in fact, providing devices with a reliable IOTS support adds realism and allows a higher degree of safety and interactivity, that allow a high number of people to take part and collaborate in a simulated scene with a very high degree of physical interaction. In this paper we introduce a novel approach for the optimization and the evaluation of movement tracking in a IOTS based system, oriented to VR/AR applications, with special focus on the training of teams. Our proposal is applied to a case study, an AR application designed to assist business buildings workers in fire extinguisher use training. Performances of our proposal are evaluated by means of a simulation, and results are validated in a test scenario based on Ultra Wide Frequency positioning by means of a simulation scenario fed with real data from anchors.

I. INTRODUCTION

Sensing position and movement of people and things is an important problem in different application fields. While applications in open range are common and well known also in the daily experience of a wide public (GPS based navigation or logistic tracking are considered commodities), there is not yet an obvious solution for closed spaces. Although it may be considered as the small scale correspondent problem, there are some specific aspects that make unapplicable the same solutions: typical applications are designed to work inside buildings, that are generally full of obstacles (besides the roof, that shields GPS signals, walls and objects also shield local radio emitters and there is electromagnetic noise because of the activities), involve human beings moving in constricted spaces (again walls, but also furnitures and objects on the floor) and require more precision (as the relevant distances are smaller). Interaction with the environment is thus crucial to provide quality services, specially when IOTS are used to track relative movements of physical objects in the space (e.g. rotation of a stick handled by a subject moving into the environment). The precision of fine movement tracking is specially important for VR/AR applications, as they involve a physical interaction of human subjects with virtual or mixed (virtual and real) objects in a real physical space, that may be not evidently perceptible, with possible harmful consequences if the environment has to be a real context. An optimal coverage of the environment by anchors, the elements that allow position and movement sensing in IOTS, is crucial for the delivery of quality services and to enhance both the realism and the safety of VR/AR applications designed to be executed in real world environments. In this paper we study an optimization and performance evaluation method for anchor positioning in a IOTS. The method is demonstrated by using real anchors that feed a specific simulation tool, in order to avoid experimentation with human subjects in the loop. The test scenario uses an Ultra Wide Band (UWB) radio based IOTS solution, but results can be generalized. The chosen application is devoted to the training of teams of non specialist personnel in their workplace, by means of an AR application, for a safe reaction in case of fire emergencies.

The paper is organized as follows: in next Section we present a short literature survey focusing on indoor positioning and tracking literature. The studied system is presented in subsequent Section III, along with the description of simulation dataset. In Section IV we present the proposed methodology, the simulation approach and the results, with a discussion of the outcomes. Conclusions follow.

II. RELATED WORKS

Indoor positioning [7] and indoor tracking [3] are two related and interconnected (actually, partially super-

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posed) application areas that specialize positioning and tracking problems to closed spaces. Indoor positioning deals with the problem of locating with precision an item in a closed space, typically a building like an office, a school, a warehouse; indoor tracking deals with the problem of contextualizing moving objects, or parts of an object, in an environment that is typically bounded by perimeter walls and in presence of obstacles, like inner walls, other fixed or moving objects or steps. Both problems refer to position or movements in a given coordinate system, that may be based on 2 or 3 dimensions.

While for open range applications GPS based solutions are ubiquous and manage to capture the most of the needs of civil applications, there is a number of different proposals that deal with the peculiarities of closed spaces. In the open range, there is generally no shielding of GPS signals; in indoor positioning and tracking, GPS signals are typically shielded, thus not available, and the system has to rely on local references, namely *anchors*. The presence of obstacles may influence anchor visibility with respect to the position of the target object. Suitable technologies should be able to operate efficiently with no harm to humans that may interact with the environment and should be able to provide high precision, to fit the scale of the environment.

Uses of indoor positioning include detection of goods in a wharehouse, location of people in a building, location of intervention points in plant maintenance, implementation of reference points along paths, presence detection of objects or animals in given areas, location dependent interactions or information delivery. Uses of indoor tracking include monitoring of parts in assembly lines or plants, security and safety monitoring, indoor navigation, indoor autonomous veichles management, warehouse automation, operations in critical or dangerous environments.

Considering radio frequency (RF) based technologies, some of the most popular for indoor positioning are active RFID [9], UWB [11], IEEE 802.11 (also known as WLAN) [5], Bluetooth [4]. Active RFID is very popular for its low cost and for the widespread use of its passive version, that allows information exchange by exploiting the electromagnetic signals exchanged between a powerless tag and a reader. In the active version, this technology is able to transmit an identification code when solicited. The range is 1-2 meters in the first case, tens of meters in the second, the cost is low. UWB

Commercial solutions exist that couple different technologies (e.g. with ultrasounds, GPS, cellular, infrared), or that use different, proprietary solutions.

For sake of space, for a comprehensive review of techniques, metrics and technologies used in indoor positioning and tracking we again suggest to refer to [7] and [3], that also provide a significant list of references.

An evaluation of algorithms for UWB indoor tracking is presented in [2]. In this paper interested readers can find a realistic evaluation of a number of different location and tracking algorithms that include trilateration, least square-multidimensional scaling, extended Kalman filter and particle filter, that are compared by using a realistic ranging model specific for UWB based devices.

III. A CASE STUDY

A. Context

Typical indoor tracking systems rely on the interactions of several devices, divided into two groups. Those belonging to the first group, usually called *anchors*, provide reference points in the physical world space and are usually placed in fixed positions. Anchors are able to communicate with one another by mean of different, manufacturers' specific, communication protocols. By exchanging messages they compute reciprocal distances by leveraging on their response times. Devices belonging to the second group, referred as *tags*, move into the portion of space covered by the communication range of the anchors. By exchanging messages with the anchors, their are able to determine their position in the defined space.

We focus our research on devices able to communicate using radio signals to transmit information, such as UWB based devices. Inference from such radio signals based measurements can be quite challenging due to a number of factors, e.g. their dependence on the relative distances/angles among the devices, environmental obstacles, signal power [3].

B. Application setup

The proposed case study concerns the implementation of IOTS features into the equipment that supports a training application. The individual has to be trained to cooperate in a team during an alarm using a fire extinguisher and consequently enact proper operations to limit the consequences, in a wider scenario such the one described in [1]. The trainee plays his role in a simulation, that is implemented by a real time immersive distributed simulator consisting of a personal support node for each team member. Personal support nodes form a peer to peer system, and provide each other the parameters about the behavior of the team member wearing them. Each node consists of a smartphone, that provides computing power, a smart sensing subsystem, that provides information about the team member and his actions, an AR/VR subsystem, providing immersive visual feedback, and an Arduino based coordinator, that controls the sensing subsystem. The smartphone runs the local software component of the distributed simulator, and produces the information for the AR/VR subsystem, that in turn visualizes the other team members and the additional simulated effects superposed to the real image observed by the perspective of the team member. The smart sensing subsystem include specific sensors placed on the dummy tools (e.g. the extinguishers) that the team members will use, to ensure that they are used properly and to provide precise information to compute their effects on the simulated fire. Further details on this simulation architecture are available in [10]. The architecture is depicted in Figure 1 (from [10]).

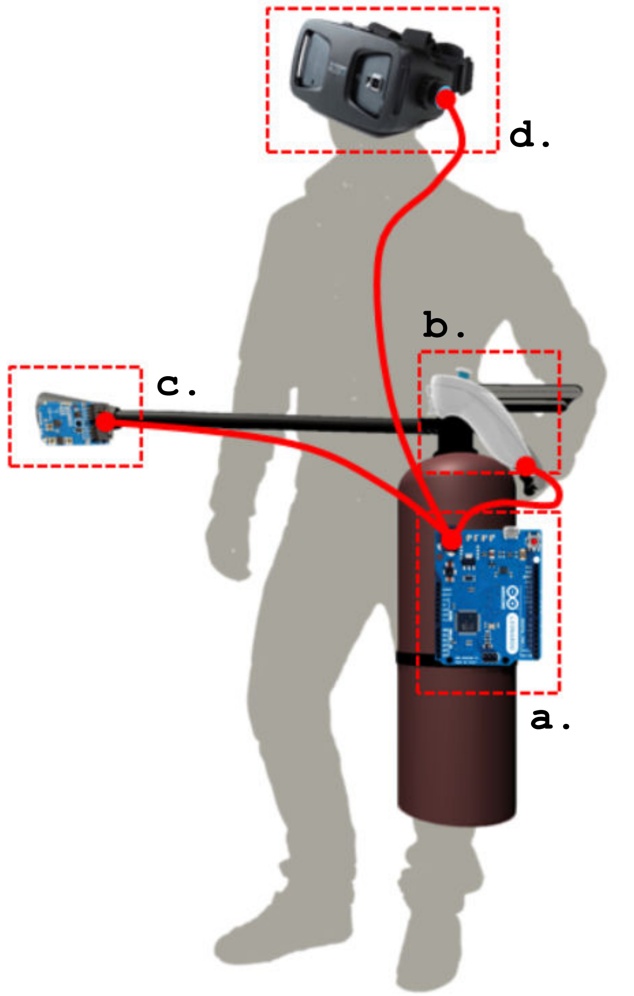


Fig. 1. Peripherals of a personal node, with a coordinator (a.), two sensors (b. and c.) and the AR device (d.)

The smart sensing subsystem also includes a receiver for IOTS, that is capable of exploiting the information coming from the anchors located in the environment. Information is provided to the smartphone, that computes the exact location by means of the proposed metric and exchanges its position with the other nodes to update the simulation and the AR/VR related information.

C. Simulation setup

The dataset for human movements simulation has been chosen among publicly available, sound repositories, collecting real or realistic profiles. The chosen dataset has been selected so to fit the data that are in practice generated by the reference IOTS, to obtain a significant simulation testbed.

This dataset, available at CMU Graphics Lab [6], is a collection of motion capture data recorded from different subjects performing different kind of activities, from sports to everyday tasks and stored in **.bvh* files[8], or Biovision Hierarchy file format. All such activities, because of the capturing tools involved, were recorded indoor thus matching our model assumptions.

Fig. 2. Tag assumed position for our model validation

From the collection, a subset of animation files were selected, in particular we focus on those animations files where the subject was involved with locomotion, especially if there was some sort of interaction the surrounding environment, and on those concerning physical activities such as sports.

The typical indoor tracking system we are investigating in this paper, as seen in Section III, leverages on the use of a tag whose position is triangulated when moving inside a delimited area. This tag is, as usual, applied to the object or person to be tracked. We consider the tag applied to the person at waist level, in close vicinity to her body as it can be seen in Figure 2. The hierarchical structure used to alter the visual appearance of a 3D character to simulate its movement is called *skeleton*. This structure is also used to store data about position and rotation of each body part, as the movement proceeds in time. The elements of this skeleton system are called *bones*, each dedicated to influence a specific portion of the character. We focused data about the hip from the dataset, the bone closest to the waist, where we assumed the tag was positioned. In Figure 3 the bone structure used in our dataset is presented.

In Figure 4 we present a sample positioning system layout. It consists primarly of a given number of UWB emitters (Figure 4-a.) acting as reference points for the tracked tag (Figure 4-b.).

During the setup of the positioning system, each anchor is required to be somehow informed about its distance with respect to the other anchors as well as from the tag (dotted gray lines in Figure 4). The anchors and tag distance from the ground is also required. To this end, a calibration sequence is performed, either man-

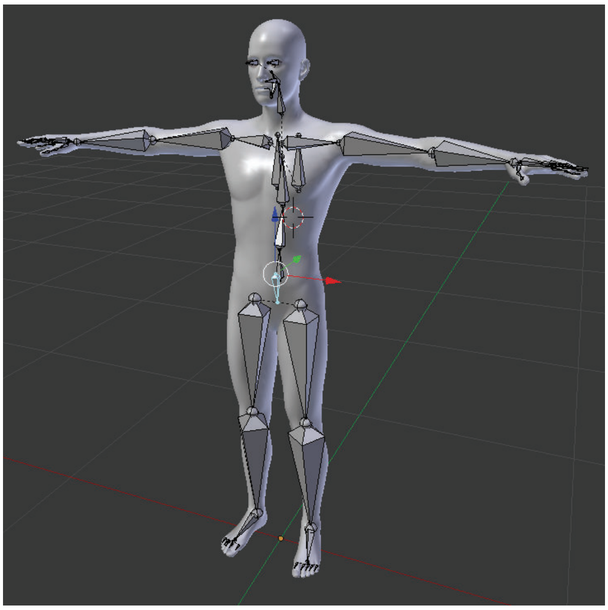


Fig. 3. The skeleton of a 3D character. Each element is called bone. Hips are highlighted in the picture

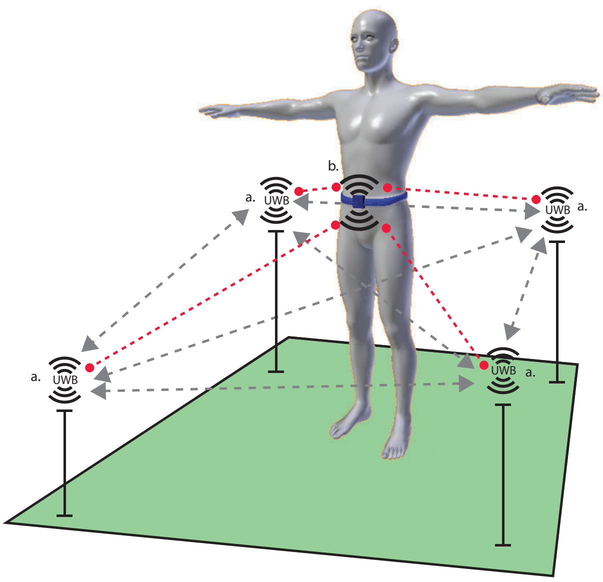


Fig. 4. A sample positioning layout

ually or automatically. In the first case, the required values are provided to the system by human intervention, in the second case an automatic process is started during which the positioning devices compute and exchange information about their relative distances.

The dotted red line represents the tag computing its position relative to the emitters once the system begins working after the calibration procedure.

IV. SIMULATION AND RESULTS

In order to simulate the tracking process, we first present a model of the distance measurement error. The rationale about the model is that it must have an area where measurement occurs at its best, and that the error increases both when the tag is too close or too far away from the anchor. In this work we first start

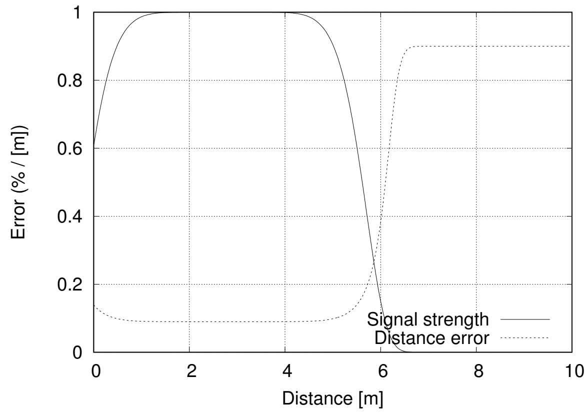


Fig. 5. Distance measurement error

evaluating this measurement quality using the following function $\eta(d)$ of the distance d between the tag and the anchor:

$$\eta(d) = e^{-\left(\frac{d-\mu}{\sigma}\right)^{\gamma}} \tag{1}$$

Parameter μ represents the best distance: the one where the measurement is more precise. Constant σ determines the width of this area, and γ the way in which it fades as the tag moves away from the anchor. In the rest of the paper we have used in Equation 1 $\mu = 2.75$, $\sigma = 2$, $\gamma = 8$. We then suppose that measurements are affected by a gaussian error of a given standard deviation $\nu(d)$ that depends on the distance d. In particular, we suppose that, when the measurement has the best quality, a standard deviation d_0 is achieved. As the quality decreases, the error becomes larger and larger, and in the worst cases it reaches $\frac{d_0}{\alpha}$ with $0 < \alpha \leq 1$. In particular we have defined $\nu(d)$ as follows:

$$\nu(d) = \frac{d_0}{\alpha + (1-\alpha)\eta(d)} \tag{2}$$

In this work we have set $d_0 = 0.09$ and $\alpha = 0.1$ in Equation 2.

Figure 5 shows the evolution of the signal strength $\eta(d)$ and of the distance error $\nu(d)$. Note that both the definitions of $\eta(d)$ and $\nu(d)$ are arbitrary and came from direct experience by working with the technology. More realistic values of ηd and νd can be obtained with an extensive measurement campaign, which was outside the scope of this work that focuses on the methodology of improving the placement of the anchor, but is planned as future work.

The tracking process is corrupted by measurement errors. Following the definition of $\nu(d)$, the error affected distances $\tilde{l}(d)$ are computed as:

$$\tilde{l}(d) = d + N(0,1) \cdot \nu(d) \tag{3}$$

Let us suppose that we have a tag in position $\mathbf{v} = (x, y, z)$. We call N_A the number of anchors: as it has been defined in literature, for having an accurate tracking, $N_A \geq 4$. Let us call $\tilde{l}_i$ the estimated distance of point $\mathbf{v}$ from anchor i, placed at coordinates

$\mathbf{v}_i = (x_i, y_i, z_i)$. We suppose that tracking is performed by a non-linear minimization process. In particular, the tracked position $\hat{\mathbf{v}} = (x, y, z)$ is selected by minimizing the following objective function $f_T(\mathbf{v})$:

$$f_T(\mathbf{v}) = \sum_{i=1}^{N_A} \left(|\mathbf{v} - \mathbf{v}_i| - \tilde{l}_i \right)^2 \tag{4}$$

The minimization step is done using *Successive Quadratic Programming* (SQP), a well known and easy to use optimization technique. In particular, for what concerns function $f_T(\mathbf{v})$, it can be particularly effective since both the gradient vector $(\frac{\partial f_T(\mathbf{v})}{\partial x}, \ldots)$ and the Hessian matrix $(\frac{\partial^2 f_T(\mathbf{v})}{\partial x \, \partial y}, \ldots)$ can be explicitly computed.

The main contribution of this work is studying a procedure for optimizing the positioning of anchors in a room, in order to obtain the best tracking results. The first issue is to find a suitable objective function that, starting from the position of the anchors, allows a non-linear optimization algorithm to find the optimal anchor placement.

This is done by simulating a tracking process, and using the obtained average tracking error as the value of the corresponding objective function. First we select a set of N_S test points $\mathbf{t}_j$ ($1 \leq j \leq N_S$): in particular we select these points from one of the traces defined in Section III-C . In order to study the average tracking error, we repeat the simulation on N_E experiments, each one involving tracking of the same N_S points, affected however by a different measuring error. This is achieved by considering an uniform set of standard normally distributed random errors $\epsilon_{ijk} \sim N(0,1)$ ($1 \leq N_A$, $1 \leq j \leq N_S$, $1 \leq k \leq N_E$) for each combination of anchor i, point j, and experiment k. Fixing the normally distributed error allows the minimization process that studies the anchor placement consistency and avoids the risk of highly variable solutions. We thus define the best position of the anchors by minimizing the following objective function $f_A(\mathbf{v}_1, \ldots, \mathbf{v}_{N_A})$:

$$f_A(\mathbf{v}_1, \ldots, \mathbf{v}_{N_A}) = \frac{1}{N_S} \frac{1}{N_E} \sum_{j=1}^{N_S} \sum_{j=1}^{N_E} \left(\mathbf{t}_j - \hat{\mathbf{t}}_{jk} \right)^2 \tag{5}$$

where $\hat{\mathbf{t}}_{jk}$ represents the result of the tracking process for test point $\mathbf{t}_j$ in simulation k, when the distance from each anchor $\mathbf{v}_i$ is affected by error ϵ_{ijk}. In particular:

$$\hat{\mathbf{t}}_{jk} = \arg\min_{\mathbf{t}} \sum_{i=1}^{N_A} \left(|\mathbf{t} - \mathbf{v}_i| - \tilde{l}_{ijk} \right)^2 \tag{6}$$

where:

$$\tilde{l}_{ijk} = |\mathbf{t}_j - \mathbf{v}_i| + \epsilon_{ijk} \cdot \nu(|\mathbf{t}_j - \mathbf{v}_i|) \tag{7}$$

Anchors are constrained to be fixed on the four walls of a rectangular room. To reduce the number of symmetries, anchors are sorted on the perimeter in a counter-clockwise order: the optimization process is constrained to maintain this order, avoiding each anchor to "overtake" the following one. Again, optimization is performed using the SQP algorithm; to avoid local minima, a random-restart procedure is used, by repeating the process several time from a different initial anchor placement.

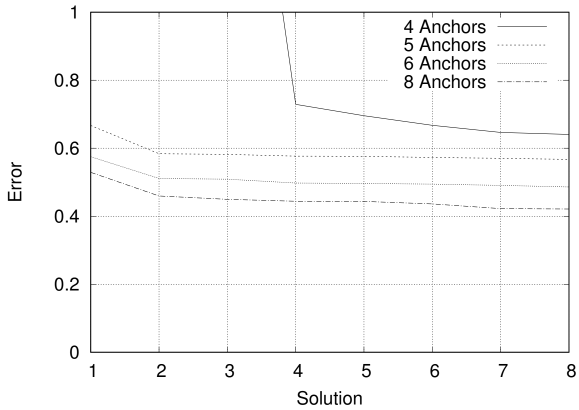


Fig. 6. Optimization of anchor placement

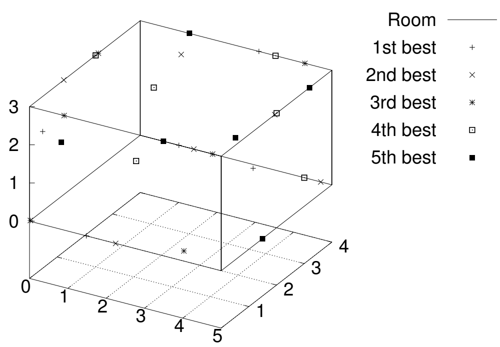


Fig. 7. Placement of the anchors in the room for the best solutions in the 6 anchor cases

Figure 6 shows the value of objective functions found at the end of each iteration of the optimization process, for a different number of anchors, and Figure 7 shows where they are placed into a 4m.×5m.×3m. large room. It is interesting to note that when the number of anchors is high, different placements can lead to equally good tracking results. However, with the minimum number of anchors ($N_A = 4$), an optimal placements of anchors is mandatory to obtain good results.

The effectiveness of the tracking process is shown in Figure 8 for different room sizes. Figures 8.a-d considers the results of the optimization procedure into 4 rooms of different sizes. As it can be seen from the spread of the tracked points from the one of the original trace, the error increases with the size of the room. In particular, Figure 8.e shows a zoomed window of the process for the smallest (S) and the largest rooms, from which it can be clearly appreciated the larger spread of the tracked points in the larger room case.

The optimization step is generally just the beginning of the tracking process: estimated position data is further

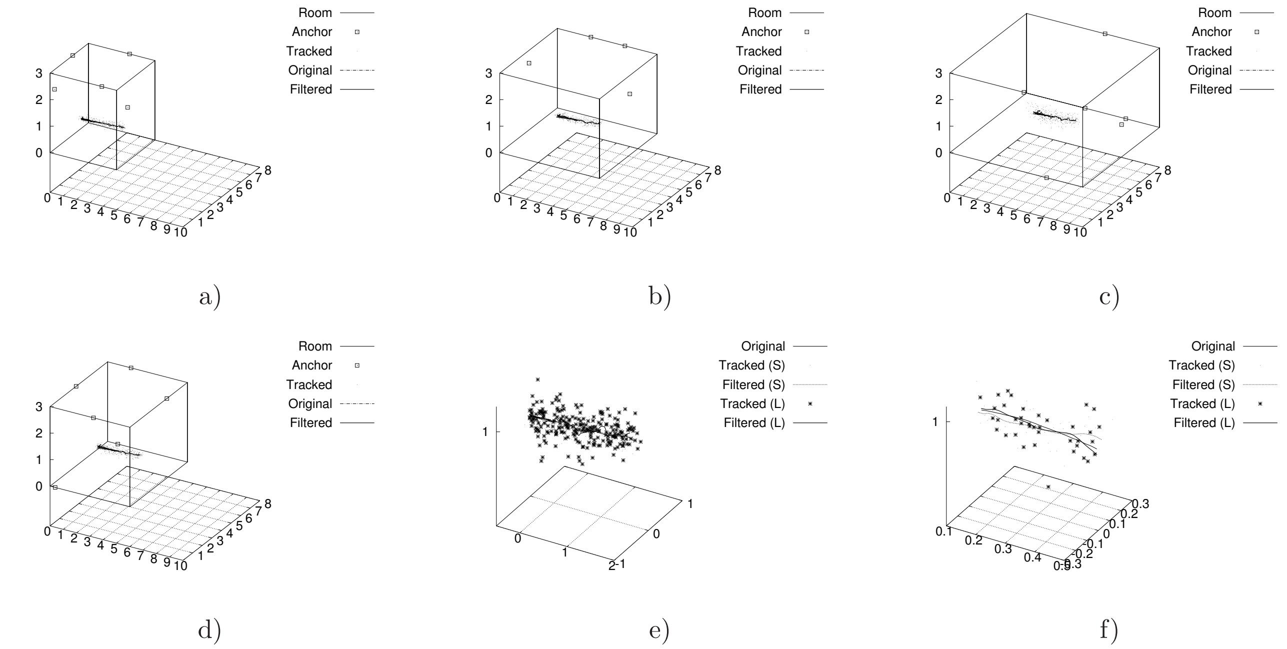


Fig. 8. Tracking process in different rooms: a) 4 × 5, b) 6 × 7.5, c) 8 × 10, d) 6 × 6, e) Zoom, f) Larger zoom

filtered to obtain more consistent and less noisy data. In many cases tags are also equipped with an IMU (Inertial Measurement Units) that includes an accelerometer, a magnetometer and a gyroscope. Elite tracking algorithms apply complex sensor fusion algorithms and Kalman filters to improve the position estimation. To simulate this process, in this work we applied a simple two pole low-pass Butterworth digital filter, centred at 0.05 of the sampling window. As it can be seen in Figure 8.f, that shows a more enlarged zoom of the tracking process, even this basic digital filter can produce results that are quite close to the original curve, independently from the room size.

To further study the effectiveness of the anchor placement process, Figure 9 reports about the application of the tracking algorithm to different data sets with the anchors placed according to the solution of the optimization process. The small room is considered in Figure 9.a for a longer linear walk, and in Figure 9.b for a dance routine. Results remains in the same error range as the one obtained during the dataset used for training. Figure 9.c considers the dance routing in the larger room: in this case it is visible that larger errors occurs when the dancer is in the outer part of the room, while results are more accurate when he is in the middle.

Figure 10 aims at studying the required number of anchors to achieve a desired level of accuracy. Without filtering, the anchor placement with the optimization produces equally good results for the three considered datasets. As expected, a larger number of anchor produces better tracking results with a lower average estimation error. However, when a good filtering algorithm is used, the number of anchors seems no longer to play an important role, and the difference between using 4 or 8 anchors become minimal. However, these results also show that the effectiveness of the filtering algorithms greatly depends on the considered trace - that is, on the type of movements performed by the tracked anchor.

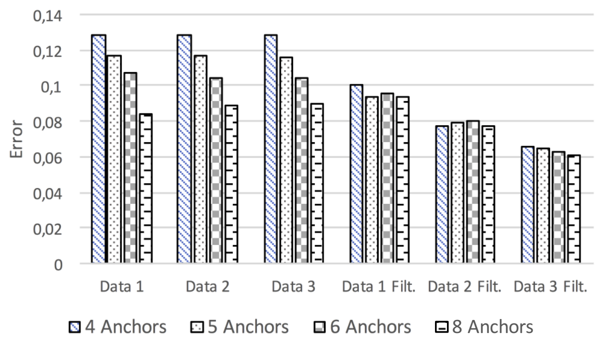
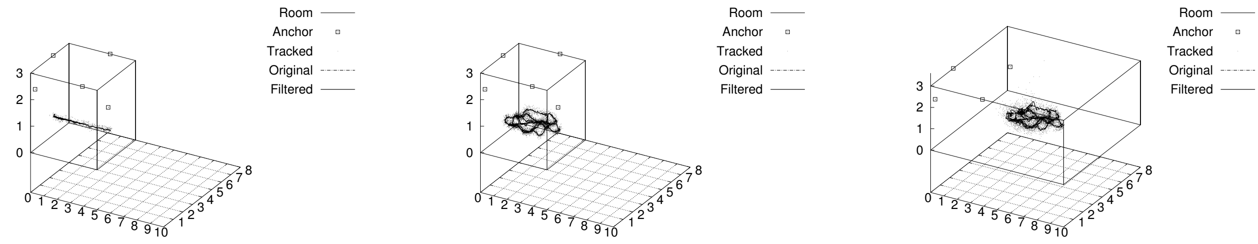


Fig. 10. Tracking error for different datasets as function of the number of anchors

V. Conclusions and Future Work

This work presented preliminary simulations that support the exploration of the effects of different anchor setups in a training application. Simulations show some interesting results, that provide a general framework in which the experimental phase of the development of the application will be set up. Results also povide a guideline for the experiments that will take place to validate simulations. Future work includes the implementation of the studied scenarios, both to validate the approach and include it into a standard application setup procedure, and to tune the system for human-in-the loop tests. More, less trivial scenarios are planned, heading to consolidate the methodology to be used in real working environments including obstacles.



a) b) c)

Fig. 9. Tracking process for different datasets: a) longer walk in a 4×5 room, b) dance in a 4×5 room, c) dance in a 8×10 room

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