Constrained LMDS Technique for Human Motion and Gesture Estimation

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Abstract—Body Area Networks is an emerging domain taking a big interest from developers and system designers. On the other hand, the need to localize is becoming necessary in diverse applications. Within this context, the aim of this paper is to estimate the different gestures and motions of the human body. Initially, we use information, about human motion, extracted from C3D files. In fact, these files provide us with the exact 3D coordinates of the sensors on a moving body. In a second step the IEEE 802.15.6 channel model is used to estimate the distances between sensors which are the input of the locomotion technique based on Multidimensional Scaling. Basically, this technique did not present satisfying results, that’s why we have improved our results by an SVD reconstruction algorithm and by adding distance constraints.

Index Terms—Body Area Networks, Cooperative Localization, Multidimensional Scaling, SVD, UWB, RSSI, IEEE 802.15.6, CM3

I. INTRODUCTION

Recently, there has been an increasing interest from researchers on a new type of network architecture known as Body Area Networks (BANs). These networks allow wireless communication between different equipments around the body in various application areas such as medicine, military applications and entertainment. These networks have a special environment due to the proximity to the body and the applications’ areas. This has a direct impact on the propagation channel characteristics [1] especially in dynamic cases [2]. The variation of the propagation channel reduces the accuracy of sensors’ localization on the human body.

A Body Area Network is formally defined by IEEE 802.15 as “a communication standard optimized for low power devices and operation on, in or around the human body (but not limited to humans) to serve a variety of applications including medicals, entertainment and others” [3]. In more common terms, a Body Area Network is a system of devices in close proximity to a person’s body that cooperate for the benefit of the user [4].

BANs aim for replacing wires around the body. Most of the time, BANs are used in applications and scenarios where different devices (sensors and other equipment) are able to gather physiological information, exchange, store and finally save or transmit data to a distant unit. The most existing BANs are related to medical applications. However BANs seek for exploring other fields such as localization, sport and multimedia.

Two types of devices are generally encountered in a BAN:

- Sensor node: a device that responds to and gather data on physical stimuli, process the data if necessary, and report the information wirelessly.
- Personal device or coordinator: a device that gathers all the information acquired by the sensors and the actuators and informs the user.

In some applications we may find another type: actuator node which acts according to data received from the sensor.

In our work, we aim to estimate the human motion by locating the position of the different sensors on the human body. The estimation is based on Multidimensional scaling and improved with imposing limits on the estimated distances and an SVD reconstruction of the distance matrix.

The rest of the document is organized as follows: In section II, the techniques used to model the human body and movement are described. The different cooperative localization techniques are then presented in section III. In section IV, the assumed scenario is presented and the simulation results are discussed. In particular, the performances of the different proposed localization techniques are compared. Finally, our concluding remarks are given in section V.

II. MODELLING OF HUMAN BODY GESTURE AND MOBILITY

The goal of our work is to estimate the human body motion and gesture. We are interested to model and obtain a complete and detailed information about the human motion. For this reason we resort to C3D (Coordinates 3D) files. In fact, this format provides a mean of storing all the raw data and other information required to interpret or analyze the raw data at a later stage. Data stored in the C3D format can provide a mean of standardizing the interchange of information and can enable multi user studies across a wide variety of manufacturers hardware and software platforms. Among the data stored in C3D files, we have the 3D coordinates of a fixed number of points, representing human body sensors at each time. The term “3D frame” consists of one or more 3D points that can be considered to be the values of the measurement variables at a single instant of time.

To summarize, a C3D file provides a fixed number of frames, representing the recording of the motion at a single instant, and each frame contains the coordinates of 3D points or sensors. For example Figure II represents a 41 points’ frame.

In the rest of this work, we exploit a C3D file of a walking human from which we extract 126 frames, containing 41
points, corresponding to one human step, since we assume, in our scenario, that human motion is periodic.

III. COOPERATIVE LOCALIZATION USING MULTIDIMENSIONAL SCALING

This section is dedicated to the main localization approach based on Multidimensional Scaling (MDS) and the different enhancement approaches.

A. Basic LMDS

Multidimensional Scaling (MDS) is a localization technique allowing sensors’ locations, knowing only the distance between each pair of points [5].

Conceptually, LMDS can be divided in three stages:
1) Distance estimation: collects and combines distance measurements into distance matrix
2) Placement: produces a set of points according to the distance matrix
3) Restoration of the coordinate system: reestablish the coordinate system by changing the basis of the set of points produced in the previous stage.

Algorithm: Let there be \( n \) sensors in a network, in our case 41, with positions \( X_i, i = 1, \ldots, n \), and \( X = [X_1, X_2, \ldots, X_n]^T \), is \( n \times m \) matrix. let \( D = [d_{ij}] \) be the \( n \times n \) matrix of pair-wise distance measurements, where \( d_{ij} \) is the distance between \( X_i \) and \( X_j \). The goal of MDS is to find an assignment to \( X \) that minimizes a cost function defined as:

\[
F(X) = \sqrt{\sum_{i=1}^{n} \sum_{j=1}^{i-1} \frac{(d_{ij} - \delta_{ij})^2}{\sum_{i=1}^{n} \sum_{j=1}^{i-1} \delta_{ij}^2}}
\]

(1)

where \( \delta_{ij} \) is the real distance between \( X_i \) and \( X_j \). The law of cosinus gives:

\[
(X_j - X_i)(X_k - X_i) = \frac{1}{2} (d_{ij}^2 + d_{ik}^2 - d_{jk}^2)
\]

(2)

If all measurements are perfect, a good way to solve the location problem is to choose some \( X_0 \) from \( X \) to be the origin of the coordinate system and construct the matrix \( B \) as follows:

\[
B = X'X'^T
\]

(3)

where \( X' = X - X_0 \).

We can solve for \( X' \) by taking an eigen decomposition of \( B \) into an orthonormal matrix of eigenvectors \( V \) and a diagonal matrix of the matching eigenvalues \( U \).

\[
B = X'X'^T = UVU^T
\]

(4)

\[
X' = UV^{1/2}
\]

(5)

In real systems, there are errors on distance measurements. For this reason MDS uses a special point in the center of the \( (X_i) \). This point is found by “double centering” the squared matrix \( D^2 \). \( B \) is given then by:

\[
B = XX^T = -\frac{1}{2}JD^2J
\]

(6)

\[
J = I - \frac{1}{n} e e^T
\]

(7)

where \( e \) is \( 1 \times n \) vector of ones. As before, the dimensionality is done by taking an eigen decomposition of \( B \) then, removing eigenvalues and eigenvectors. This is a safe operation since \( B \) is symmetric positive definite, and therefore it has \( n \) positive eigenvalues.

\[
B = XX^T = UVU^T
\]

(8)

\[
X = UV^{1/2}
\]

(9)

Thus, MDS provides a method of converting a complete matrix of distance measurements to a matching topology in 2 or 3D coordinate systems.

B. Proposed enhancements

In order to improve the LMDS results we propose two approaches. The first consists in using a part of the distance matrix (the most reliable component) and reconstruct it. The second introduce constraints on the estimated distances.

1) SVD reconstruction: Because of the very high shadowing introduced by the human tissue, the distance matrix may presents wrong values and in some cases unreal. Hence the idea is to use an incomplete distance matrix, containing the most reliable values. The incomplete distance matrix must be reconstructed in order to obtain a complete one which is necessary as an input to the LMDS algorithm which will be applied as a final step.

The reconstruction algorithm is based on [6] and the fact that, in 3D coordinate system, the rank of a distance matrix cannot exceeds 5. As a consequence, well chosen 10\( n \) entries are quite enough to rebuild the distance matrix.

For the sampling task, a general and realistic model is described in [6] and includes a disk model setting \( p_{ij} \approx 1 \) if \( d_{ij} \leq R \) and \( p_{ij} \approx 0 \) otherwise. Here \( R \) denotes the sensor radius and \( p_{ij} \in [0,1] \) denotes the probability that
node \(i\) has successfully measured its exact distance to node \(j\). Another assumption concerning the detection probability was \(p_{ij} \geq p_c > 0\) for all \(i, j = 1 \ldots n\), for some small positive constant \(p_c\). In words, we assume that even far away sensors have a very small non-zero probability of detecting their distance.

At this level we obtain the incomplete estimated distance matrix \(\hat{D}\) given by:

\[
\hat{D}_{ij} = \begin{cases} 
\frac{d_{ij}^2 + \epsilon_{ij}}{\gamma_{ij}} & \text{with probability } p_{ij} \\
\frac{\gamma_{ij}}{1 - p_{ij}} & \text{with probability } 1 - p_{ij}
\end{cases}
\]

(10)

The \(?\) denotes that the entry is unknown.

The reconstruction algorithm takes as input the incomplete distance matrix \(\hat{D}\) and as a first step we construct \(S\):

\[
\hat{S}_{ij} = \begin{cases} 
\frac{d_{ij}^2 + \epsilon_{ij} + \gamma_{ij} (1 - p_{ij})}{p_{ij}} & \text{if } d_{ij} \text{ was detected} \\
\frac{\gamma_{ij}}{1 - p_{ij}} & \text{otherwise}
\end{cases}
\]

(11)

\(\gamma_{ij}\) represent “the best guess” for the distance between \(i\) and \(j\) where there is no detection. In our simulations the best guess is forced to the maximum connectivity radius \(R^2\).

The next step is the construction of \(S^*_5\), the best rank 5 approximation to \(S\), recall, that \(D\) has rank at most 5. And the last step is to apply LMDS algorithm with input \(S^*_5\).

2) Distance constraints: Another way to improve the estimation results consists in adding constraints on estimated distances. Since the sensors are on the body surface, not all the distances are allowed. For every estimated distance, maximum and minimum limits are specified and the estimation results are compared to these constraints. If the estimated distance exceeds these limits, the estimator is forced on the maximum or the minimum. To do that, two extreme cases are proposed. In the first case, we assume having details on every link. Indeed, the maximum and minimum distance between each pair of sensors is known. However in the second, the information are more general where we have only one maximum distance constraint. These constraints allow to reduce the shadowing effect introduced by the human tissues on the estimated distances.

IV. SCENARIO, SIMULATIONS, RESULTS AND DISCUSSIONS

A. Scenario

The proposed scenario consists in a moving human body on which we set up a fixed number of sensors on the surface. The real coordinates of these sensors are given by a C3D file while the estimated coordinates are the output of LMDS algorithm which takes as input the observed distances deduced from the RSSI (Radio Signal Strength Indicator). In BANs, the structure of the channel model for scenarios involving, for example, body surface and implant is not similar. And for this reason, the IEEE 802.15.6 standard identify different scenarios relative to communication type and the frequency band. In our simulations, we used the path loss model proposed by IEEE 802.15.6 standard relative to body surface to body surface communications (CM3: Channel Model 3) and UWB technology [7].

The path loss is modeled by the following equation:

\[
PL(d)[dB] = a \log_{10}(d) + b + N
\]

(12)

where \(PL\) is the path loss in \(dB\), \(a\) and \(b\) are coefficients of linear fitting, \(d(mm)\) is the distance between the TX and the RX, and \(N\) is normally distributed variable with zero mean and standard deviation \(\sigma_N\), which models the shadowing. In channel model 3 case, these parameters take the values presented in the table 1 and the measurements conditions are given by [8]:

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>(a)</td>
<td>19.2</td>
</tr>
<tr>
<td>(b)</td>
<td>3.38</td>
</tr>
<tr>
<td>(\sigma_N)</td>
<td>4.40</td>
</tr>
</tbody>
</table>

TABLE 1: CM3 parameters

The most interesting thing about this model is that the relative path gain represents the variation of the path loss with the respect to the mean value of the standing scenario. In fact the transmitting antenna is placed on the navel while the receiving is on different positions on the body and the human subject takes different positions: standing, walking, up and down movements.

Based on RSSI, the goal is to estimate, at each moment and so for each frame, the location of these sensors to track the person’s motion.

As presented before, the two first stages of LMDS algorithm give the coordinates in an arbitrary basis, that’s why, we assume the knowledge of three sensors’ locations to reestablish the real coordinates system. These reference points may be located with four UWB devices in the environment from which they measure 4 TOA accurate perform localization.

The Figure 2 presents a scenario of distant human health care and motion tracking, where the PDA should collect the information about distances and transmit them to experts to be analysed.

![Fig. 2: Example of human locomotion tracking](image_url)

B. Simulations’ setup

The LMDS algorithm was simulated under some specific conditions. In fact, we used 126 frames, containing 41 points...
or sensors, from a C3D file representing a walking human. For SVD reconstruction algorithm we pick antenna radius $R = 500mm$ and the minimum detection probability $p_e = 0.01$. For distance constraint, we propose two cases:

- Case 1: we assume having full information about maximum and minimum distances for each pairwise sensors.
- Case 2: we possess only a maximum distance that all links cannot exceed which is in our simulations 2 meters.

C. Results and discussions

Our results are presented by snapshots of the human motions where we represent the real sensors coordinates and the estimated positions relative to the basic techniques, namely, LMDS, and the different proposed enhancements.

The Figure 3 shows the results of applying LMDS algorithm on the estimated distance from RSSI and taking into account the shadowing introduced by the human tissues. The average position error per frame is around $217mm$ (This average is calculated over one step equivalent to 126 frames and 1000 iterations). As the figure shows the results are not satisfying and for that reason we introduced some enhancements.

The first amelioration is presented by the Figure 4 where we see a diminution of estimation errors that may cause the total loss of the human shape and the average error is now about $167mm$ which represent a 22% improvement. And the Figure 5 represents the estimated coordinates result of LMDS technique with both SVD reconstruction and distance constraints (case 1). The Figure shows a significant improvement since we estimate relatively the body shape with an average positioning error per frame equal to $37mm$. Compared with LMDS, this is a 76% improvement.

![Fig. 3: Estimated frame obtained with LMDS vs real frame.](image)

![Fig. 4: Estimated frame obtained with LMDS and SVD vs real frame.](image)

![Fig. 5: Estimated frame obtained with LMDS, SVD and distance constraints (case 1) vs real frame](image)

Under the same simulation conditions used in different previous sections, the goal is, now, to compare the different approaches. For this purpose, we represent the Cumulative Distribution Function (CDF) relative to each method. The Figure 6 represents the different CDFs of different techniques. The positioning error represents the average error per frame.

The Figure shows that for LMDS algorithm, 80% of errors are lower than $250mm$, while for LMDS with SVD and distance constraints the value is reduced to $50mm$. For LMDS with SVD reconstruction and LMDS with distance constraints, the figure shows that, for certain error values distance constraints method gives better results, because clipping reduces shadowing effect.

Figure 6 is obtained by using case 1 for distance constraint. In fact the information used in case 1 about distance is not always available. That’s why we simulate the other extreme case where we know only one distance constraints for all links. The results are shown on the Figure 7.

As shown, the improvement is not considerable and the most remarkable thing is that with SVD reconstruction this constraint has no effect. This may be explained by the fact that in SVD reconstruction algorithm, we implicitly enforce a limit on the distances.

In fact the advantage of these constraints, even if their contribution is minimal, is the reduction of the shadowing effect introduced by the human body and the elimination of unreal estimated distances. And of course, the improvement depends on the manner of clipping applied on estimated distances. For Case 1, we want to insist that this kind of
These results show the wide range we have, thanks to the change of distance information level, especially with the distance matrix characteristics and the constraints that may emerge from this matrix.

V. Conclusion

The principal goals of this work were the modeling of the human motion and the use of the LMDS algorithm to estimate the body motion, which was not really enough. Therefore, we introduced SVD reconstruction algorithm and we added some constraints on estimated distances. By the end, we have different techniques to estimate the body motion. In addition, the performance of these techniques have been evaluated and compared using realistic modelling of both mobility and channel.

In future works, the intention is to investigate the communication between access points and the coordinator element in BAN. This work should go further than this step to studying inter BANs communications and the group navigation. Regarding the mobility level, the next task is to focus on social models which can improve BAN’s performances specially in cooperative scenarios and the extracted information from C3D files may be combined with the usual mobility models such as Random Walk and we will obtain not only the human body mobility model but also the pattern traced by the different body sensors. In this context we opt to the Levy Flight Model since it is very similar to the human mobility [9].

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