Magnetic Field based Indoor Positioning Using the Bag of Words Paradigm

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***Abstract*—In this paper, A Bag of Words based method is presented to test a magnetic field based indoor positioning method. The Indoor positioning problem is solved as a pattern recognition problem, where each reference point is a different class. Feature vectors are constructed using a simplified bag of words methodology allowing user speed invariance. Several well known classifiers have been used to test the proposed method obtaining promising results when recognition the position of the user.**

I. Introduction

Indoor positioning approaches can be categorized as infrastructure-based and infrastructure-less technologies [1]. The alternatives based on the former category require the deployment of custom beacons and instrumentation to sense the environment, whereas the systems based on the latter category use signals already present in the environment.

Magnetic field based indoor positioning [2] is an interesting infrastructure-less approach which is based on the uniqueness of the disturbances in the magnetic field produced by the structural elements present in a scenario. The uniqueness of the disturbances can be used as fingerprint since it is stable over time. The only requirement is that the device used to provide indoor localization, such as modern mobile phones, has to include a magnetometer to measure the magnetic field strength. This is one of the main reasons why magnetic field based methods are becoming popular in the last years.

The magnetometer provides a 3D vector that corresponds to the strength and direction of the magnetic field measured at a particular location. For each location, the three components of the measured magnetic field $[Mag_x, Mag_y, Mag_z]$ can be used as fingerprint for localization purposes. However, the use of several consecutive measurements as fingerprint provides more accurate results [3]. In this case, comparing two fingerprints is equivalent to comparing three pairs of 2D curves.

The user speed is one of the main issues when using a continuous fingerprint. Figure 1 shows the values recorded (with a sampling period of 0.02 seconds) for Mag_x component while the user was walking through a corridor at different speeds. The user took approximately 50 (blue), 81 (green) and 35 (red) seconds to cross the corridor. The three curves are different on the number of consecutive values recorded and it makes it difficult the direct comparison among them. Figure 2 shows the same curves with different scales on the x-axis (time), so the curves have the same width and can be visually compared. It can be observed that the three curves are very similar in shape. Therefore, a new representation of the shape of the curve, being invariant to the user speed, is needed to allow a direct comparison among different continuous fingerprints. This representation must mainly consider the shape of the curves instead of the values themselves. A similar behavior is reported when comparing the other two components Mag_y and Mag_z.

In this paper, a Bag of Words (BoW) based method is proposed to characterize magnetic field based fingerprints allowing user speed invariance. The BoW model is commonly used in text classification problems where a text is represented as the bag of its words, disregarding grammar and word order but keeping multiplicity. A histogram with the frequencies of the occurrences of each word is used as a feature vector to feed a classifier. The BoW model has been also adapted to other domains such as image [4], [5] and video classification [6].

Positioning is formulated as a pattern recognition problem, where for each location, a featured vector is obtained using a simplified BoW based technique. It consists of characterizing several consecutive magnetic field measurements observed in the neighborhood of the location by coding the shape of the curves. The resulting pattern recognition problem has as many classes as different locations exist in the scenario.

The main contribution of this paper is the use of a BoW based strategy to characterize magnetic field based samples allowing user speed invariance. As far as we known, this is the first time that such as techniques have been used in the magnetic field based indoor localization research field. In particular, the proposed approach has been tested in a scenario consisting of a corridor with 21 different locations. This process has been repeated 10 times, varying the user speed. A Leaving One Out (LOO) strategy has been performed to obtain an estimation of the accuracy when recognizing the locations using well-known classifiers. In addition, an estimation of the localization error has been also obtained. Promising results have been obtained in terms of both, recognition accuracy and localization error. Note that the proposed method only use magnetic field measurements to provide indoor localization.

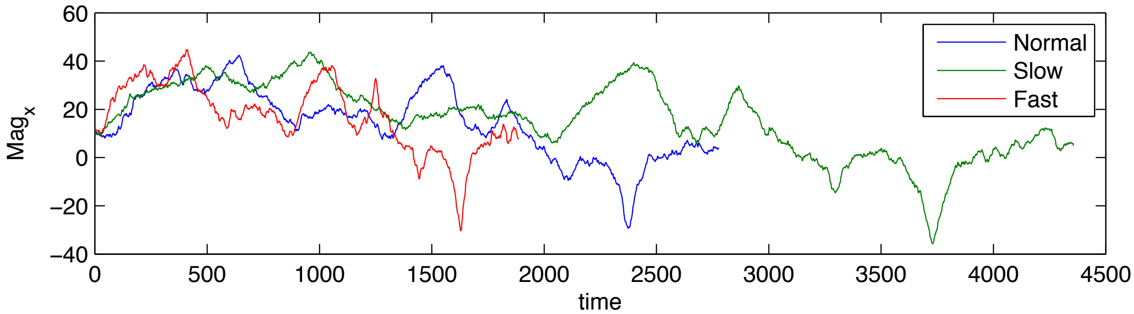

Fig. 1. Magnetic field values recorded (with a sampling period of 0.02 seconds) while the user was walking through the same corridor at normal (blue), slow (green) and fast speed (red). Only Mag_x component is showed.

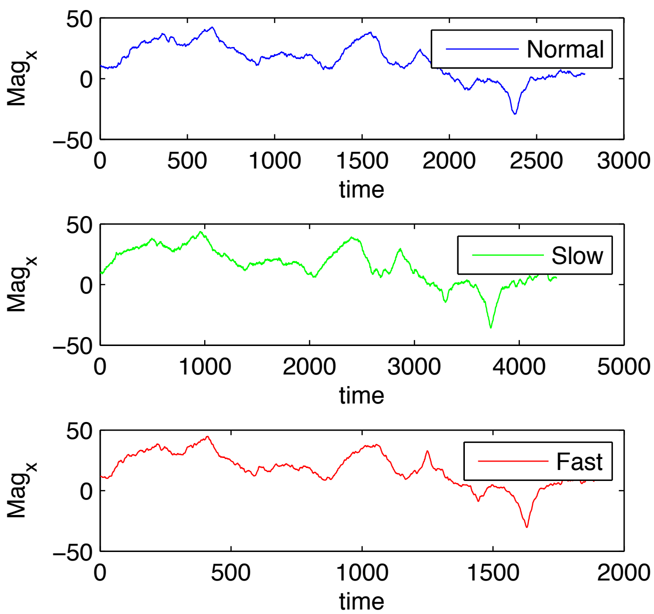

Fig. 2. The same curves than the ones showed in Figure 1 but now different scales on x-axis has been used, so the curves have the same width and can be visually compared.

The rest of the paper is organized as follows. Section II presents a review of some of the most important research works related with this paper. Section III explains the methodology proposed to deal with the localization problem. Experiments and the results obtained are explained in Section IV. Finally, Section V presents the most important conclusions arisen from this work.

II. Related work

There are many papers in the literature dealing with magnetic field based methods for indoor localization problems. Some of the most important are: [2], [3], [7], [8], [9], [10], [11], [12], [13] among others.

One of the first papers using magnetic field to provide indoor localization is [2] where authors fully studied how feasible is the use of magnetic field for indoor positioning. For this purpose, they studied the stability of the indoor geomagnetic field over a long period of time, and concluded that the intensity of the Earth's magnetic field change depending of the location, mainly because of the presence of steel structural elements, ferromagnetic objects and the electronic devices typically found in each location. This fact is precisely what makes very interesting indoor positioning method based on the use of magnetic field measurements, since it provides an advantage for distinguishing different locations inside a scenario. They also concluded that better results can be obtained in scenarios with a big number of elements able to modified the magnetic field with respect to other scenarios with a low number of electronic or ferrous infrastructures.

Regarding which data provided by the magnetometer should be used, on the hand hand, in [8], [11], [12] the authors demonstrated that magnetic field based localization performs better when the three components of the magnetic field are considered, which can be crucial in scenarios with low magnetic field variability. On the other hand, authors in [3] showed that it preferable, in terms of localization error, the use of several consecutive magnetic field measurements instead of using just one discrete capture, since the former provide more discriminative capacity than the latter.

Regarding the accuracy level demanded, for some application a room level accuracy is enough. This is the case of [13], where authors presented a method to provide room level accuracy where for each location (room), a signature is taken from a random walk inside the room. This signature consists of the components of the frequency spectrum of the magnetic signal, obtained from the Fourier transform of the signal. However, room level accuracy can be not enough for many practical applications.

Some works, as for instance in [11], used more than one professional magnetometers to measure the magnetic field. However, state of art methods such as [12], [13] used the magnetometer include in actual mobile phones. The latter is a preferable option, since it allows more people accessing to this technology.

In this paper, the three components of the magnetic field and continuous data are used to characterize each location. The magnetometer included in actual mobile phones is used to capture the data. The method is tested in a corridor with 21 different locations with the idea of providing a magnetic field based indoor positioning method able to estimate the user location with high accuracy.

III. Methods

A. Background on Bag-of-Words

In order to introduce the BoW technique, we firstly state the definition of some key concepts. The entity termed *word* is the basic unit of discrete data defined as an item of a vocabulary Ω of size V, $\Omega = \{w_1, \ldots, w_V\}$. A *corpus* Π is a collection of M documents, $\Pi = \{d_1, \ldots, d_M\}$, being a *document* d_j a sequence of N_j words. A word w_i ($i \in \{1, \ldots, V\}$) is repeated $q(w_i, d_j)$ times in a document d_j. Therefore, $N_j = \sum_{w_i \in \Omega}(q(w_i, d_j))$.

The BoW technique consists of characterizing a document as a histogram of word frequencies, i.e. each bin of the histogram stores the probability of a particular word appearing in a given document: $P(w_i|d_j) = q(w_i, d_j)/N_j$. The document d_j can be characterized using the feature vector λ_j as defined in Eq. 1.

$$\lambda_j = [P(w_1|d_j), \ldots, P(w_V|d_j)] \tag{1}$$

B. Bag-of-Words in our problem

In our problem, a document d_j is related to a location, and it is obtained using several consecutive magnetic field measurements captured in its neighborhood. Figure 3 shows an example of a document, where the three components of the magnetic field in the neighborhood of a location are taken into account. A word is a descriptor of the shape of the small portions of the curves that form part of the documents. In the traditional BoW technique, the vocabulary is automatically obtained by means of a clustering process in the training corpus. In our case, a simplified version is used instead, where the vocabulary Ω is set to a fixed predefined set of $V = 5$ words: $\Omega = \{w_{\nearrow}, w_{\searrow}, w_{\leftrightarrow}, w_{\cap}, w_{\cup}\}$. The meaning of these words is as follows:

- $w_{\nearrow}$: The curve increases the value.
- $w_{\searrow}$: The curve decreases the value.
- $w_{\leftrightarrow}$: The value of the curve is almost constant.
- $w_{\cap}$: The curve has a strong maximum in the middle.
- $w_{\cup}$: The curve has a strong minimum in the middle.

Using the proposed vocabulary Ω, the Mag_x component of the document showed in the Figure 3 can be mainly explained with the words: $w_{\nearrow}$, $w_{\leftrightarrow}$ and $w_{\searrow}$; the Mag_y component with: $w_{\leftrightarrow}$, $w_{\cap}$ and $w_{\searrow}$; and finally the Mag_z component with: $w_{\leftrightarrow}$, $w_{\searrow}$ and $w_{\nearrow}$.

C. Methodology overview

Figure 4 shows a scheme of the proposed methodology. Given the three components $[Mag_x, Mag_y, Mag_z]$ of the magnetic field measured in an environment, a window of size α ($\alpha = 200$ in this example) is selected for each location to extract a document. In particular, the α previous magnetic field measurements to the one measured just when the user was in this location, have been chosen. For each location there is a document.

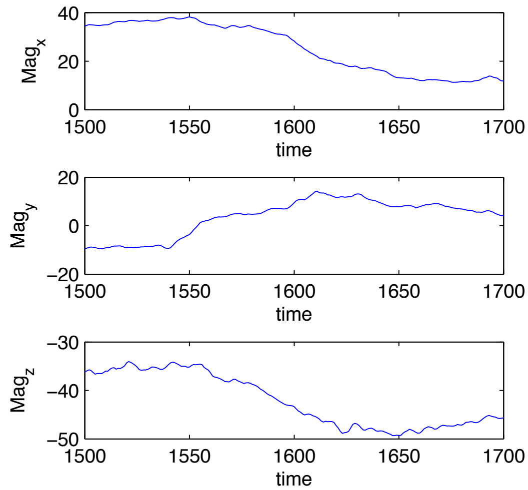

Fig. 3. Example of a document. It is a set of three 2D curves.

Each document is divided using a sliding window of size β ($\beta = 50$ in this example). For each extracted window, the shape of the curve is studied to decide which word, from the ones belonging to the vocabulary Ω, has the most similar shape (see Section III-D). For instance, in the example showed in Figure 4, four different small curves have been extracted for each component ($N_j = 4$). Note that in this example, no overlapping has been used. Regarding Mag_x component, the first window corresponds to the word $w_{\nearrow}$, the fourth to $w_{\leftrightarrow}$, and the second and third to $w_{\searrow}$. Regarding Mag_y component, the first and second windows correspond to $w_{\nearrow}$, the third to $w_{\cap}$ and the fourth to $w_{\searrow}$. Finally, Regarding Mag_z component, the second and third windows correspond to $w_{\searrow}$, the first to $w_{\leftrightarrow}$ and the fourth to $w_{\nearrow}$.

For each component, a histogram is created (of size V) where each bin stores the probability of a particular word appearing in a given component of the document (see Eq. 1). They can be calculated in this example as follows:

- $\lambda_j^x = [0.25, 0.5, 0.25, 0.0, 0.0]$,
- $\lambda_j^y = [0.5, 0.25, 0.0, 0.25, 0.0]$,
- $\lambda_j^z = [0.25, 0.5, 0.25, 0.0, 0.0]$.

The final feature vector λ_j is the concatenation of the histograms of frequencies of each component and therefore the feature vector λ_j of each document d_j has 15 elements ($V = 5$ and $5 \times 3 = 15$). Note that the final feature vector is obtained using only data provided by a mobile phone magnetometer.

D. Word assignment

In order to obtain the most similar word from Ω, each extracted curve is halved into two parts. The slopes of the lines, resulting of performing a linear regression with the points belonging of each part of the curve, are studied. The extracted curve is assigned to a word using the followings rules:

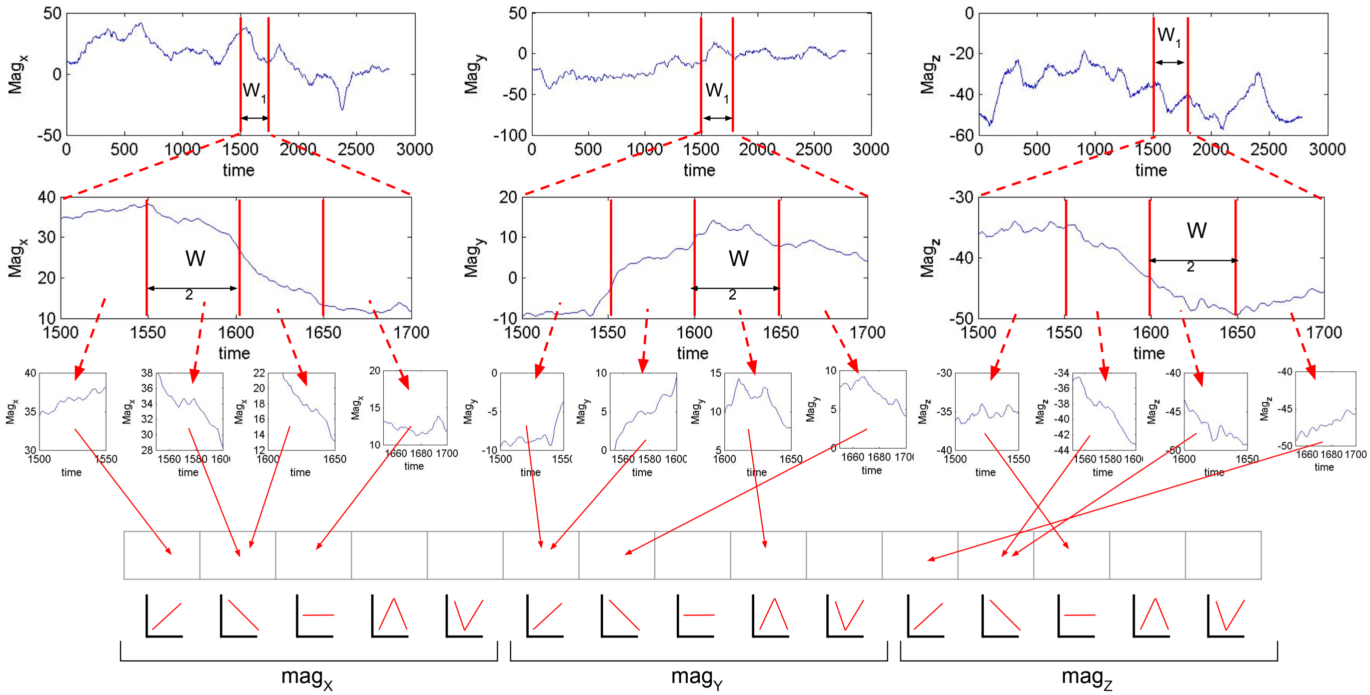

Fig. 4. Scheme of the proposed methodology. Top curve are the three components $[Mag_x, Mag_y, Mag_z]$ of the magnetic field measured for the complete corridor. Middle curves are the document extracted (with size $\alpha = 200$) for a particular location. Bottom curves show the subwindows of size $\beta = 50$ extracted from each component of the document. In this example, no overlapping is used, then four small windows are extracted for each component. Each one of these subwindows contributes to one of the bins of the BoW histogram.

- If $S_1 > \gamma_+$ and $S_2 > \gamma_+ \rightarrow w_{\nearrow}$
- If $S_1 < \gamma_-$ and $S_2 < \gamma_- \rightarrow w_{\searrow}$
- If $S_1 > \gamma_+$ and $S_2 < \gamma_- \rightarrow w_{\cap}$
- If $S_1 < \gamma_-$ and $S_2 > \gamma_+ \rightarrow w_{\cup}$
- Otherwise $\rightarrow w_{\leftrightarrow}$

where S_1 and S_2 are the slopes of estimated regression lines of the first and second part of the curve, and γ_+ and γ_- are two threshold values.

Figure 5 shows two examples of this process. In the top case, $S_1 = -0.17$ and $S = -0.22$, i.e. the curves shows a clear descending shape, this is the reason to assign this curve to the word $w_{\searrow}$. However, in the bottom example, $S_1 = -0.05$ and $S = 0.08$. Therefore, the word to be assigned will be determined depending on the values of the thresholds γ_+ and γ_-. The most probable one is $w_{\leftrightarrow}$ since the curve remains almost constant.

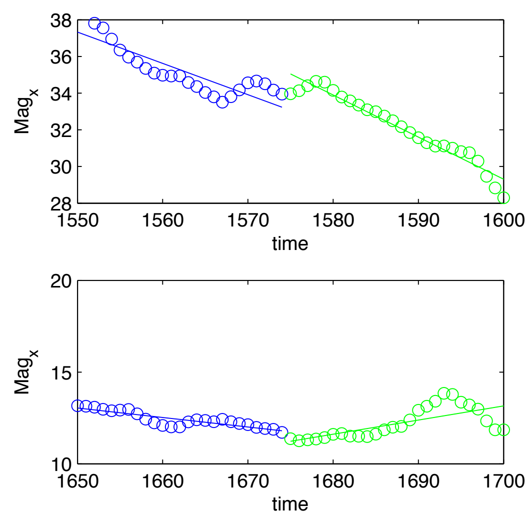

Fig. 5. Two Examples of how is determined the most similar word. Blue and green dots are the measurements belonging to the first and the second part, respectively of the curves. In top example, the calculated slopes are $S_1 = -0.17$ and $S_2 = -0.22$ showing a clear descending shape ($w_{\searrow}$ word). In the bottom one, the calculated slopes are $S_1 = -0.05$ and $S_2 = 0.08$. In this case, it is not so clear which is the word to be assigned. It can be $w_{\cup}$ or $w_{\leftrightarrow}$ depending on the thresholds γ_+ and γ_-.

E. Dealing with user's velocity

To deal with user's velocity is a problem similar to the problem of obtaining image corners, invariant to change of scales, in object recognition techniques [14]. In [14] several detection windows with different sizes were used to deal with the change of scale problem. Inspired by this idea, we proposed to use several sizes α to extract the documents from the raw magnetic field values. Therefore, instead of using just one α size to extract the documents, a set of different sizes $A = \{\alpha_1, \ldots, \alpha_r\}$ can be used. The more different sizes we have, the more likely we are to capture the user's speed correctly. But having a lot of different sizes can slow down the localization algorithm. The exact number of different sizes r should be a compromise between the two factors previously commented.

F. The localization problem as a pattern recognition problem

Given the three components $[Mag_x, Mag_y, Mag_z]$ of the magnetic field measured in a scenario and given a list of l desired localization to be taken into account, a set of r documents is extracted for each location. Therefore, the corpus Π has $l \times r$ different documents. For each document d_j, a feature vector λ_j is obtained (see Section III-C). The label of each feature vector is the location identifier. Note that each location has r feature vectors with the same label, each one obtained using a different size α_i, $\alpha_i \in A$. Note also, that all feature vectors, regardless of size α_i used, has the same dimension ($V \times 3$).

The obtained feature vectors can be used to feed a classifier. Then the positioning problem can be transformed to a classical pattern recognition one, where there exists several training samples that are used to train a classifier (feature vectors λ_j). After, given a feature vector with an unknown label (i.e. an unknown location), the trained classifier can be used to estimate the label and therefore to know the location.

Given the magnetic field data from an unknown location (test sample), the proposed methodology is applied (see Section III-C) to obtain the corresponding r feature vectors. Then, for each feature vector a label is obtained using the previously trained classifier. The final label is obtained by a simple voting procedure.

In contrast to such pattern recognition with only two classes (commonly called as *binary* problems), the classification problem to be solved in this work is a non trivial problem, since there can be a lot of different classes depending on the number of different location in the scenario. Despite this fact, the proposed way of characterizing magnetic field fingerprints allows to obtain good accurate results in the proposed scenario.

G. Background on supervised classifiers

In this work, the distance-based classifier k-Nearest Neighbor (k-NN) [15], the learning-based classifier Support Vector Machine (SVM) [16] and the ensemble learning-based classifier Random Forest (RF) [17] have been used to test the proposed approach. In the three cases, multiclass version of the classifiers have been used. They are briefly explained as follows:

The k-Nearest Neighbor (k-NN) [15] method consists of assigning a new test sample to the class most frequently represented among the k closest instances in the training set according to a certain dissimilarity measure.

The learning-based classifier Support Vector Machine (SVM) [16] uses a kernel to transform the original data into a higher dimensional space where a hyperplane that optimally separates the data into two categories is found. In fact, this is the hyperplane that maximizes the distance between two parallel hyperplanes separating the data. The larger the margin between these parallel hyperplanes, the better the generalization error of the classifier will be. Many kernel mapping functions can be used, from which the two most common ones[1] have been chosen: a Linear Function (LF) and a Radial Basis Function (RBF). Each kernel has different parameters that must be tuned beforehand to best fit a given problem. For the chosen kernels, LF has the parameter C standing for the margin size of the hyperplane. Large C values force the optimization to avoid misclassified samples by a small margin, while small C values allow to misclassify some sample with a larger margin for the sake of generalization ability. On the other hand, RBF kernel also has the C parameter but also has a σ parameter which controls the width of the Gaussian kernel. A small σ may result in a good training error rate (over-fitting) but it does not generalize. On the contrary, a large value of σ converts RBF into an almost linear kernel.

The ensemble learning-based classifier Random Forest (RF) [17] is an ensemble classifier using many decision tree models, the predictions of which are combined by majority voting to produce a single output. Each decision tree is constructed by using a random subset of the features used for training with replacement. In our case, a subset of the elements that compounds the λ_j feature vector. The best split on the selected random features is used to split the node of each decision tree, since it minimizes the number of misclassified training points. This procedure is repeated until every node is pure, i.e. can not be spited again. Random trees can be efficiently generated, and the combination of large sets of random trees generally lead to accurate and even non-linear models.

IV. Experiments

A. Database

As far as we known, there is only one public database with magnetic field data [3]. However, since magnetic field data was captured, in this dataset, almost at the same user speed, we decide to capture a new dataset to test the proposed user speed invariant approach.

A corridor of a building of our university has been selected as scenario to test the proposed approach. A user captured magnetic field measurements while was walking though the corridor with a sampling period of 0.02 seconds. An Android application in a Google Nexus 5 mobile phone was used to capture the data. A total of 21 reference points have been selected (see Figure 6). The corridor is 76 meters long, approximately.

This process was repeated 10 times varying the user speed velocity. Table I shows the number of samples and the time needed to cross the corridor for the 10 paths. Note that in the first four paths, the user walked at *normal* velocity. In the fifth, sixth, seventh and eighth ones the user moved very slow, slow, fast and very fast, respectively. In the ninth path, the user moved first slow and in the middle changed to fast speed. In the tenth, the user did the opposite.

[1] In this work, the LIBSVM library [18] has been used, which provides an implementation of a broad variety of kernels.

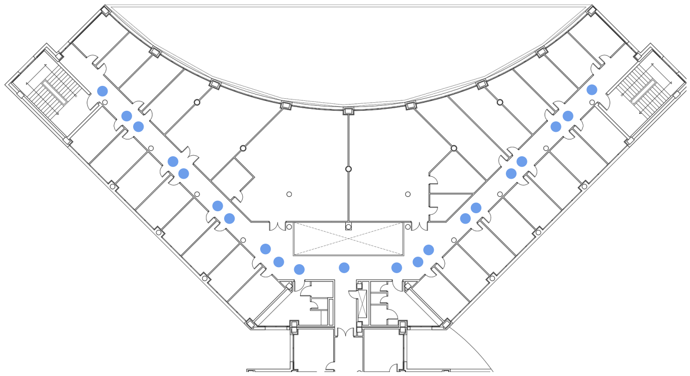

Fig. 6. Map of the proposed scenario. Blue dots represent the 21 locations used in the experiments.

TABLE I
NUMBER OF SAMPLES AND THE TIME NEEDED TO CROSS THE CORRIDOR FOR THE 10 PATHS.

Path	#samples	Time	Speed
1	2777	50.38	Normal
2	2655	48.47	Normal
3	2765	50.48	Normal
4	2674	48.01	Normal
5	4356	81.11	Very slow
6	3272	60.97	Slow
7	2240	40.18	Fast
8	1887	35.13	Very fast
9	2465	45.24	1st slow, 2nd fast
10	2365	45.02	1st fast, 2nd slow

B. Experimental Setup

In order to deal with the different user speed problem, the set of sizes A has been set to $A = \{50, 100, 150, 200\}$ that approximately corresponds to the last $1, 2, 3$ and 4 seconds of data just before arriving to the location. Therefore, four ($r = 4$) different feature vectors are calculated for each location.

Some other parameters have been set (see Section III) as follows:

- $\beta = 50$, with overlapping each 5 samples.
- $\gamma_+ = 0.1$
- $\gamma_- = -0.1$

Four different k-values have been tested when using the k-NN classifier, $K = \{1, 3, 5, 7\}$. For tuning SVM parameters, in the case of LF kernel, C parameter is tuned via 5-fold cross-validation (in the training set) looking for its best value C_0 by a coarse grid search with its value ranging $\{2^{-10}, 2^{-9}, ..., 2^{10}\}$. Then we do a fine grid search to find the best C value in $\{2^{C_0-1.8}, 2^{C_0-1.7}, ..., 2^{C_0+1.8}\}$. For RBF kernel, a two layer grid search has been used instead, as there are two parameters C and σ. C values are sought in the same ranges as before, but σ values range $\{2^{-13}, 2^{-12}, ..., 2^{3}\}$ in the coarse grid search resulting in σ_0 value, and it ranges $\{2^{\sigma_0-1.8}, 2^{\sigma_0-1.7}, ..., 2^{\sigma_0+1.8}\}$ in the fine grid search. RF tends not to over-fit independently of the number of trees, however the study in [19] states that the number of trees ν affects the learned model and it should be tuned. Therefore, the best ν value is tuned via 5-fold cross validation (in the training set) by a coarse grid search with ν_0 value ranging $\{100, 500, 900, ..., 2100\}$. Then a fine grid search is performed to find the best ν value in $\{\nu_0 - 300, \nu_0 - 200, ..., \nu_0 + 300\}$.

A Leaving One Out (LOO) error estimation method has been used. Since there are 10 different paths, in each step of the LOO process, 9 paths have been used for training and just one for testing. In each step, the accuracy in the problem of recognizing the location has been obtained. The total accuracy of the method is the mean of the 10 steps. Localization error between the real position of the location and the estimated one can be also estimated since the real location of the 21 reference points is known. Therefore, for each LOO step, the mean localization error in meter is also obtained. Since SVM and RF and classifiers use some random processes in the training phase, each experiment has been repeated 10 times.

C. Results

Table II shows the results obtained. In general, all the classifiers (with the exception of SVM with LF kernel) have obtained good results in terms of recognition accuracy and localization error. The best result is obtained using the RF classifier with an accuracy of 76.2% and a localization error of 3.33 meters. The 5-NN classifier also obtains good results and even slightly better in terms of localization error, reaching 3.11 meters of mean error. As it has been commented previously, the proposed problem is a 21 class pattern recognition problem. However, the proposed methodology is able to recognize more than three out of four locations. In addition, the localization error obtained is competitive, in a similar scenario, to other localization algorithms based in other technologies as for instance WiFi-based methods [20].

In this experiment, no distance restriction has been applied, i.e. for each location, the most similar one is looked at the complete training database. In real problems, it is expected that the next location of the user should be close in space from the actual one. Then, the experiment has been repeated but now only training samples in a radius of a particular number of meters ϵ have been taken into account. Two radius values ϵ has been used: 10 and 5 meters. In this case, only k-NN classifier has been used since to train RF and SVM in real time can significantly slow down the localization algorithm.

Table III shows the results obtained. As expected, the accuracy increases when distance restriction are applied reaching 88.5% when $\epsilon = 10$ meters distance restriction has been applied, and 93.5% when $\epsilon = 5$ meters one has been used instead. The localization error has also significantly improved reaching a mean error of 0.64 meters with the 7-NN classifier with $\epsilon = 10$, and of only 0.22 meters with the 5-NN classifier with $\epsilon = 5$.

V. CONCLUSIONS

In this paper, a Bag of Words (BoW) based method has been proposed to characterize magnetic field based fingerprints allowing user speed invariance. It has been tested in a scenario consisting of a corridor with 21 different locations. This

TABLE II

MEAN ACCURACY AND MEAN LOCALIZATION ERROR OBTAINED WITH ALL CLASSIFIERS. THE BEST RESULT HAS BEEN HIGHLIGHTED.

Classifier	mean accuracy	Mean localization error
1-NN	0.7000 ± 0.1315	$3.97 \pm 1.65m$
3-NN	0.7400 ± 0.1246	$3.46 \pm 1.11m$
5-NN	0.7600 ± 0.1280	$\mathbf{3.11 \pm 1.47}m$
7-NN	0.7350 ± 0.1355	$3.85 \pm 1.87m$
RF	$\mathbf{0.7630 \pm 0.1124}$	$3.33 \pm 1.13m$
SVM LF	0.6910 ± 0.0966	$5.17 \pm 1.31m$
SVM RBF	0.7440 ± 0.1014	$3.77 \pm 1.37m$

TABLE III

MEAN ACCURACY AND MEAN LOCALIZATION ERROR OBTAINED WHEN DISTANCE RESTRICTIONS ARE TAKEN INTO ACCOUNT WITH $\epsilon = 10m$. THE BEST RESULTS HAVE BEEN HIGHLIGHTED.

Classifier	accuracy	mean localization error
1-NN	0.8550 ± 0.0984	$0.70 \pm 0.45m$
3-NN	0.8800 ± 0.0891	$0.66 \pm 0.41m$
5-NN	0.8800 ± 0.0982	$0.68 \pm 0.42m$
7-NN	$\mathbf{0.8850 \pm 0.0958}$	$\mathbf{0.64 \pm 0.42}m$

process has been repeated 10 times, varying the user speed. A Leaving One Out (LOO) strategy has been performed to obtain an estimation of the accuracy when recognizing the locations using well-known classifiers. Promising results have been obtained in terms of recognition accuracy and localization error and even better when space restrictions have been applied.

Future work must focus in applied the proposed method in a real time localization method. It should be also of interest to study which is the effect of the parameters of the method (α, β, γ_+ and γ_-) in the accuracy. Finally, to compare the proposed methodology with other ways of comparing magnetic field fingerprints, as for instance the use of dynamic time warping (DTW) distance function should be also addressed.

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TABLE IV

MEAN ACCURACY AND MEAN LOCALIZATION ERROR OBTAINED WHEN DISTANCE RESTRICTIONS ARE TAKEN INTO ACCOUNT WITH $\epsilon = 5m$. THE BEST RESULTS HAVE BEEN HIGHLIGHTED.

Classifier	accuracy	mean localization error
1-NN	0.9200 ± 0.0718	$0.22 \pm 0.26m$
3-NN	0.9300 ± 0.0854	$0.22 \pm 0.31m$
5-NN	$\mathbf{0.9350 \pm 0.0827}$	$\mathbf{0.22 \pm 0.30}m$
7-NN	0.9300 ± 0.0775	$0.25 \pm 0.29m$

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