Predicting User Movements in Heterogeneous Indoor Environments by Reservoir Computing*

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Abstract

Anticipating user localization by making accurate predictions on its indoor movement patterns is a fundamental challenge for achieving higher degrees of personalization and reactivity in smart-home environments. We propose an approach to real-time movement forecasting founding on the efficient Reservoir Computing paradigm, predicting user movements based on streams of Received Signal Strengths collected by wireless motes distributed in the home environment. The ability of the system to generalize its predictive performance to unseen ambient configurations is experimentally assessed in challenging conditions, comprising external test scenarios collected in home environments that are not included in the training set. Experimental results suggest that the system can effectively generalize acquired knowledge to novel smart-home setups, thereby delivering an higher level of personalization while decreasing costs for installation and setup.

1 Introduction

Localization and tracking of mobile users in indoor environments are important services in the construction of smart spaces, and they are even considered enabling, baseline services for Ambient Assisted Living (AAL) [AAL, 2009] applications. In fact, AAL aims at improving the quality of life of elderly or disabled people, by assisting them in their daily life, in order to preserve their autonomy and by making them feeling included, protected and secure in the places where they live or work (typically their home, their office, the hospital and any other places where they may spend significant part of their time). These objectives can be granted only if the appropriate services are delivered to the users in the right time and in the right pace.

In AAL applications, localization aims at the real time estimation of the user position, while tracking refers to the activity of reconstructing the path of the user, with the purpose of anticipating its future position and thus to prepare the system to the timely delivery of the appropriate services. Localization and tracking of objects can be achieved by means of a large number of different technologies, however only few of them are suitable for AAL applications, as they should be non-invasive on the users, they must be suited to the deployment in the user houses at a reasonable cost, and they should be accepted by the users themselves. On the other hand, accuracy in the position estimation is subject to less requirements than it may occur in other applications (accuracies in the order of the centimeter or below are typically not required). Considering all these constraints, a promising technology for this services is based on Wireless sensor networks (WSN) [Baronti *et al.*, 2007], due to their properties of cost and time effective deployment. Within such WSN, it is possible to estimate the location of a user by exploiting Received Signal Strength (RSS) information, that is a measure of the power of a received radio signal that can be obtained from almost any wireless device.

The measurement of RSS values over time provides information on the user trajectory under the form of a time series of sampled signal strength. The relationship between the RSS and the location of the tracked object cannot be easily formulated into an analytical model, as it strongly depends on the characteristics of the environment as well as on the wireless devices involved. In this sense, computational learning models have received much interest as they allow to learn such relationship directly from the data. These approaches typically exploit probabilistic learning techniques to learn a probabilistic estimate of user location given RSS measurements at known location [Zàruba *et al.*, 2007]. However, such models have considerable computational costs connected both with the learning and the inference phase, which might grow exponentially with the number of sensors in the area. Further they do little to exploit the sequential nature of the RSS streams, whereas they provide static pictures of the actual state of the environment. There exist several machine learning approaches capable of explicitly dealing with signals characterized by such time-dependent dynamics including, for instance, probabilistic Hidden Markov Models (HMM), Recurrent Neural Networks (RNN) and kernel methods for sequences. In this paper, we focus on a computationally efficient neural paradigm for modeling of RNNs, that is known as Reservoir Computing (RC). In particular, we con-

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sider Echo State Networks (ESNs) [Jaeger and Haas, 2004; Jaeger, 2001], that are dynamical neural networks used for sequence processing. The contractive reservoir dynamics provides a fading memory of past inputs, allowing the network to intrinsically discriminate among different input histories [Jaeger, 2001] in a suffix-based fashion [Tiño *et al.*, 2007; Gallicchio and Micheli, 2011], even in absence of training.

The most striking feature of ESNs is its efficiency: training is limited to the linear outputs whereas the reservoir is fixed; additionally, the cost of input encoding scales linearly with the length of the sequence for both training and test. In this regard, the ESN approach compares favorably with competitive state-of-the-art learning models for sequence domains, including general RNNs, in which the dynamic recurrent part is trained, e.g. [Kolen and Kremer, 2001], probabilistic Hidden Markov Models, that pay consistent additional inference costs also at test time, and Kernel Methods for sequences, whose cost scales at least quadratically with the input length, e.g. [Gärtner, 2003]). ESNs have been successfully applied to several tasks in the area of sequence processing, often outperforming other state-of-the-art learning models (see [Jaeger and Haas, 2004; Jaeger, 2001]). Recently, ESNs have shown good potential in a range of tasks related to autonomous systems modeling, e.g. as regards event detection and localization in robot navigation [Antonelo *et al.*, 2008; 2007] and multiple robot behavior modeling [Waegeman *et al.*, 2009]. However, such applications are mostly focused on modeling robot behaviors and often use artificial data obtained by simulators.

In this paper, we apply the ESN approach to a real-world scenario for user indoor movements forecasting, using real and noisy RSS input data, paving the way for potential applications in the field of AAL. The experimental assessment is intended to show that the proposed technology has a strong potential to be deployed in real-life situations, in particular as regards the ability of generalizing the prediction performance to unknown environments. In this sense, we expect that the proposed solution will increase the level of service personalization by making accurate prediction of the user spatial context, while yielding to a reduction of the setup and installation costs thanks to its generalization capability.

2 User Movement Prediction in Indoor Environments

2.1 Localization by Received Signal Strength

The exploitation of wireless communication technologies for user localization in indoor environments has recently received much attention by the scientific community, due to the potential of service personalization involved in an accurate identification of the user spatial context. Cost efficiency is a critical aspect in order to determine the success of such localization technologies. In this sense, the most promising localization approaches are certainly those based on Received Signal Strength (RSS) information, that is a measure of the power of a received radio signal. RSS measurements can be readily obtained from (potentially) any wireless communication device, being a standard feature in most radio equipments. In a, not so far-ahead, scenario, we foresee an ubiquitous diffusion of wireless sensors in the environment (e.g. monitoring temperature, humidity, pollution, etc.), together with a wide availability of radio devices on the user's body (e.g. personal electronics, sensors monitoring health status, etc.). Therefore, irrespectively of the intended use of such sensors and devices, we expect to be able to exploit their radio apparatus to obtain noisy, yet potentially informative, RSS traces for realtime user localization.

Indoor positioning systems based on RSS information are getting increasing attention due to the widespread deployment of WLAN infrastructures, given that RSS measures are available in every 802.11 interface. Mainly, we distinguish between two alternative approaches to localize users leveraging the RSS measurements, i.e. *model-based* and *fingerprinting* positioning. Model-based positioning is popular approach in literature that founds on expressing radio frequency signal attenuation using specific path loss models [Barsocchi *et al.*, 2011]. Given an observed RSS measurement, these methods triangulate the person based on distance calculations from multiple access points. However, the relationship between the user position and the RSS information is highly complex and can hardly be modeled due to multipath, metal reflection, and interference noise. Thus, RSS propagation may not be adequately captured by a fixed invariant model. Differently from model-based approaches, fingerprinting techniques, such as [Kushki *et al.*, 2007], create a radio map of the environment based on RSS measurements at known positions throughout an offline map-generation phase. Clearly, the localization performance of fingerprinting-based model relies heavily on the choice of the distance function that is used to compute the similarity between the RSS measured in the online phase, with the known RSS fingerprints. Further, the offline-generated ground truth needs to be revised in case of changes to the room/environment configuration which result in relevant discrepancies in the known fingerprints.

The user localization approaches discussed above focus on finding accurate estimates of the current user position, but lack the ability of anticipating his/her future location. Being capable of predicting the future user context is of fundamental value to enhance the reactivity and personalization of smart services in indoor environments. In the following, we describe a real-life office scenario targeted at adaptive user movement prediction using RSS traces: a brief discussion of the wireless technology involved is provided together with a detailed description of the experimental indoor environment.

2.2 Movement Prediction Scenario

A measurement campaign has been performed on the first floor of the the ISTI institute of CNR in the Pisa Research Area, in Italy. The scenario is a typical office environments comprising 6 rooms with different geometry, arranged into pairs such that coupled rooms (referred as Room 1 and Room 2 in the following) have fronting doors divided by an hallway, as depicted in Fig. 1. Rooms contain typical office furniture: desks, chairs, cabinets, monitors that are asymmetrically arranged. From the point of view of wireless communications, this is a harsh environment due the to multi-path reflections caused by walls and the interference produced by electronic

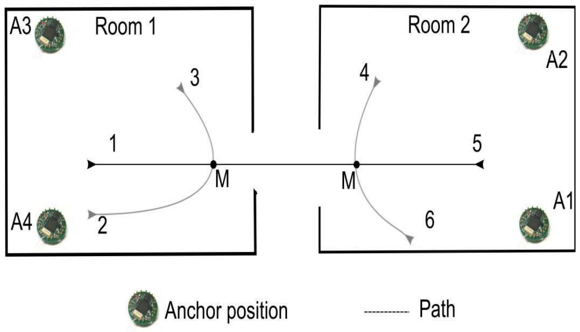

Figure 1: Schematic view of the experimental setting: anchors' position and prototypical user movements are shown. Straight paths, labeled as 1 and 5, yield to a room change, while curved movement (paths 2, 3, 4 and 6) preserve the spatial context. The M markers denote the points where we predict if the user is about to change its location. The actual setting differs from the schematics by the presence of office furniture (covering roughly 50% of the space) that is asymmetrically arranged and influences the actual user trajectories in the different rooms.

Dataset Number	length [m]	width [m]
1	4.5	12.6
2	4.5	13.2
3	4	12.6

Table 1: Physical layout of the 3 room couples.

devices. Experimental measurements have been performed by a sensor network of 5 IRIS nodes[1] embedding a Chipcon AT86RF230 radio subsystem that implements the IEEE 802.15.4 standard. Four sensors, in the following *anchors*, are located in fixed positions in the environment and one sensor is placed on the user, hereafter called *mobile*.

The measurement campaign comprises experiments on three different couple of rooms with a total surface spanning from 50 m^2 to about 60 m^2. Table 1 details the environment dimensions for the three couple of rooms, hereby referred as dataset 1, dataset 2 and dataset 3. Experiments consisted in measuring the RSS between anchors and mobile for a set of repeated user movements. Figure 1 shows the anchors deployed in the environment as well as a prototypical trajectory for each type of user movement. The height of the anchors has been set to $1.5m$ from the ground and the mobile was worn on the chest. The measurements were carried out on free paths to facilitate a constant speed of the user of about 1 m/s. Measures denote RSS samples (integer values ranging from 0 to 100) collected by sending a beacon packet from the anchors to the mobile at regular intervals, 8 times per second, using the full transmission power of the IRIS.

Experimentation gathered information on 6 prototypical paths that are shown in Fig. 1 with arrows numbered from 1 to 6: two movement types are considered for the prediction task, that are straight and curved trajectories. The former run from Room 1 to Room 2 or viceversa (paths 1 and 5 in Fig. 1) and yield to a change in the spatial context of the user, while curved movements (paths 2, 3, 4 and 6 in Fig. 1) preserve the spatial context. Table 2 summarizes the statistics of the collected movement types for each dataset: due to physical constraints, dataset 1 does not have a curved movement in Room 1 (path 3). The number of trajectories leading to a room change, with respect to those that preserve the spatial context, is indicated in Table 2 as "Tot. Change" and "Tot. Unchanged", respectively. Each path produces a trace of RSS measurements that begins from the corresponding arrow and that is marked when the user reaches a point (denoted with M in Fig. 1) located at $0.6m$ from the door. Overall, the experiment produced about 5000 RSS samples from each of the 4 anchors and for each dataset. The marker M is the same for all the movements, therefore different paths cannot be distinguished based only on the RSS values collected at M.

Path Type	Dataset 1	Dataset 2	Dataset 3
1	26	26	27
2	26	13	12
3	-	13	12
4	13	14	13
5	26	26	27
6	13	14	13
Tot. Changed	52	52	54
Tot. Unchanged	52	54	50
Lengths *min-max*	19-32	34-119	29-129

Table 2: Statistics of the collected user movements.

The experimental scenario and the gathered RSS measures can naturally be exploited to formalize a binary classification task on time series for movements forecasting. The RSS values from the four anchors are organized into sequences of varying length (see Table 2) corresponding to trajectory measurements from the starting point until marker M. A target classification label is associated to each input sequence to indicate wether the user is about to change its location (room) or not. In particular, target class $+1$ is associated to location changing movements (i.e. paths 1 and 5 in Fig. 1), while label -1 is used to denote location preserving trajectories (i.e. paths $2, 3, 4$ and 6 in Fig. 1). The resulting dataset is made publicly available for download[2].

3 Reservoir Computing for Movement Prediction

Reservoir Computing (RC) is a computational paradigm covering several models in the Recurrent Neural Network (RNN) family, that are characterized by the presence of a large and sparsely connected hidden *reservoir* layer of recurrent non-linear units, that are read by means of some read-out mechanism, i.e. typically a linear combination of the reservoir

[1] Crossbow Technology Inc., `http://www.xbow.com`

[2] `http://wnlab.isti.cnr.it/paolo/index.php/dataset/6rooms`

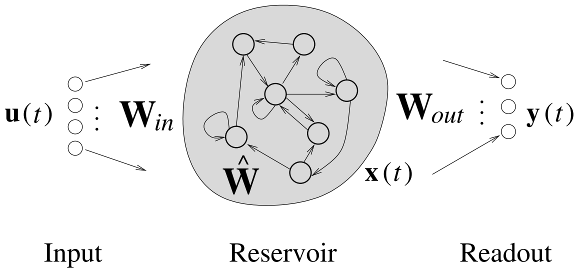

Figure 2: The architecture of an ESN: $\mathbf{W}_{in}$, $\hat{\mathbf{W}}$ and $\mathbf{W}_{out}$ denote the input, the reservoir and the output weights, respectively. Terms $\mathbf{u}(t)$ and $\mathbf{y}(t)$ identify the input at time t and the corresponding predicted read-out; $\mathbf{x}(t)$ is the associated reservoir state. Further details are given in the text.

outputs. With respect to traditional RNN training, where all weights are adapted, RC performs learning mainly on the output weights, leaving those in the reservoir untrained. As other RNNs, RC models are well suited to modeling of dynamical systems and, in particular, to temporal data processing. As the movement prediction problem discussed in this paper is, from a machine learning perspective, a time-series prediction task, we are naturally interested in analyzing and discussing the effectiveness of the RC paradigm on such a scenario. In particular, we focus on the computationally efficient ESNs [Jaeger, 2001; Jaeger and Haas, 2004; Lukosevicius and Jaeger, 2009], that are one of the best known RC models, that are characterized by an input layer of N_U units, an hidden reservoir layer of N_R *untrained recurrent non-linear units* and a *readout* layer of N_Y feed-forward linear units (see Fig. 2). Within a time-series prediction task, the untrained reservoir acts as a *fixed* non-linear temporal expansion function, implementing an encoding process of the input sequence into a state space where the trained linear readout is applied.

Standard ESN reservoirs are built from simple additive units with a sigmoid activation function which, however, has been shown to weakly model the temporal evolution of slow dynamical systems [Jaeger *et al.*, 2007]. In particular, [Gallicchio *et al.*, 2011] have shown that indoor user movements can be best modeled by a *leaky integrator* type of RC network (LI-ESNs) [Jaeger *et al.*, 2007]. Given an input sequence $\mathbf{s} = [\mathbf{u}(1), \ldots, \mathbf{u}(n)]$ over the input space $\mathbb{R}^{N_U}$, at each time step $t = 1, \ldots, n$, the LI-ESN reservoir computes the following state transition

$$\mathbf{x}(t) = (1-a)\mathbf{x}(t-1) + af(\mathbf{W}_{in}\mathbf{u}(t) + \hat{\mathbf{W}}\mathbf{x}(t-1)), \quad (1)$$

where $\mathbf{x}(t) \in \mathbb{R}^{N_R}$ denotes the reservoir state (i.e. the output of the reservoir units) at time step t, $\mathbf{W}_{in} \in \mathbb{R}^{N_R \times N_U}$ is the input-to-reservoir weight matrix (possibly including a bias term), $\hat{\mathbf{W}} \in \mathbb{R}^{N_R \times N_R}$ is the (sparse) recurrent reservoir weight matrix and f is the component-wise applied activation function of the reservoir units (we use $f \equiv tanh$). The temporal recursion in (1) is based on a null initial state, i.e. $\mathbf{x}(0) = \mathbf{0} \in \mathbb{R}^{N_R}$. The term $a \in [0, 1]$ is a *leaking rate* parameter, which is used to control the speed of the reservoir dynamics, with small values of a resulting in reservoirs that react slowly to the input [Jaeger *et al.*, 2007; Lukosevicius and Jaeger, 2009]. Compared to the standard ESN model, LI-ESN applies an exponential moving average to the state values produced by the reservoir units (i.e. $\mathbf{x}(t)$), resulting in a low-pass filter of the reservoir activations that allows the network to better handle input signals that change slowly with respect to the sampling frequency. LI-ESN state dynamics are therefore more suitable for representing the history of input signals.

For a binary classification task over sequential data, the linear readout is applied only after the encoding process computed by the reservoir is terminated, by using

$$\mathbf{y}(\mathbf{s}) = sgn(\mathbf{W}_{out}\mathbf{x}(n)), \quad (2)$$

where sgn is a sign threshold function returning $+1$ for non-negative arguments and -1 otherwise, $\mathbf{y}(\mathbf{s}) \in \{-1, +1\}^{N_Y}$ is the output classification computed for the input sequence $\mathbf{s}$ and $\mathbf{W}_{out} \in \mathbb{R}^{N_Y \times N_R}$ is the reservoir-to-output weight matrix (possibly including a bias term).

The reservoir is initialized to satisfy the so called *Echo State Property* (ESP) [Jaeger, 2001]. The ESP asserts that the reservoir state of an ESN driven by a long input sequence only depends on the input sequence itself. Dependencies on the initial states are progressively forgotten after an initial *transient* (the reservoir provides an echo of the input signal). A sufficient and a necessary condition for the reservoir initialization are given in [Jaeger, 2001]. Usually, only the necessary condition is used for reservoir initialization, whereas the sufficient condition is often too restrictive [Jaeger, 2001]. The necessary condition for the ESP is that the system governing the reservoir dynamics of (1) is locally asymptotically stable around the zero state $\mathbf{0} \in \mathbb{R}^{N_R}$. By setting $\tilde{\mathbf{W}} = (1-a)\mathbf{I} + a\hat{\mathbf{W}}$, where a is the leaking rate parameter, the necessary condition is satisfied whenever the following constraint holds:

$$\rho(\tilde{\mathbf{W}}) < 1 \quad (3)$$

where $\rho(\tilde{\mathbf{W}})$ is the *spectral radius* of $\tilde{\mathbf{W}}$. Matrices $\mathbf{W}_{in}$ and $\hat{\mathbf{W}}$ are therefore randomly initialized from a uniform distribution, and $\hat{\mathbf{W}}$ is successively scaled such that (3) holds. In practice, values of ρ close to 1 are commonly used, leading to reservoir dynamics close to the edge of chaos, often resulting in the best performance in applications (e.g. [Jaeger, 2001]).

In sequence classification tasks, each training sequence is presented to the reservoir for a number of $N_{transient}$ consecutive times, to account for the initial transient. The final reservoir states corresponding to the training sequences are collected in the columns of matrix $\mathbf{X}$, while the vector $\mathbf{y}_{target}$ contains the corresponding target classifications (at the end of each sequence). The linear readout is therefore trained to solve the least squares linear regression problem

$$\min \|\mathbf{W}_{out}\mathbf{X} - \mathbf{y}_{target}\|_2^2 \quad (4)$$

Usually, Moore-Penrose pseudo-inversion of matrix $\mathbf{X}$ or ridge regression are used to train the readout [Lukosevicius and Jaeger, 2009].

4 Experimental Evaluation

We evaluate the effectiveness of the RC approach to user movement prediction on the real-life scenario described in Section 2.2. In particular, we assess the ability of the proposed approach to generalize its prediction to unseen indoor environments, which is a fundamental property for the deployment as a movement prediction system in real-life applications. To this end, we define an experimental evaluation setup where RC training is performed on RSS measurements corresponding to only 4 out of 6 rooms of the scenario, while the remaining 2 offices are used to test the generalization capability of the RC model.

In [Gallicchio *et al.*, 2011], it has been analyzed the baseline performance of different ESN models on user movement prediction with a small 2-rooms dataset. Such an analysis suggests that the LI-ESN model, described in Section 3, is best suited to deal with slowly changing RSS time series. Therefore, in the remainder of the section, we limit our analysis to the assessment of a leaky-integrated model, with metaparameters chosen as in [Gallicchio *et al.*, 2011]. In particular, we consider LI-ESNs comprising reservoirs of $N_R = 500$ units and a 10% of randomly generated connectivity, spectral radius $\rho = 0.99$, input weights in $[-1, 1]$ and leaking rate $a = 0.1$. Results refer to the average of 10 independent and randomly guessed reservoirs. The readout ($N_Y = 1$) is trained using pseudo-inversion and ridge regression with regularization parameter $\lambda \in \{10^{-i} | i = 1, 3, 5, 7\}$.

Input data comprises time series of 4 dimensional RSS measurements (N_U = 4) corresponding to the 4 anchors in Fig. 1, normalized in the range $[-1, 1]$ independently for each dataset in Table 1. Normalized RSS sequences are feed to the LI-ESN network only until the marker signal M. To account for the the initial reservoir transient, each input sequence is presented consequently for 3 times to the networks.

We have defined 2 experimental settings (ES) that are intended to assess the predictive performance of the LI-ESNs when training/test data comes from both uniform (ES1) and previously unseen ambient configurations (ES2), i.e. providing an external test set. To this aim, in ES1, we have merged datasets 1 and 2 to form a single dataset of 210 sequences. A training set of size 168 and a test set of size 42 have been obtained for the ES1, with stratification on the path types. The readout regularization parameter $\lambda = 10^{-1}$ has been selected in the ES1, on a (33%) validation set extracted from the training samples. In ES2, we have used the LI-ESN with the readout regularization selected in the ES1, and we have trained it on the union of datasets 1 and 2 (i.e. 4 rooms), using dataset 3 as an external test set (with measurements from 2 unknown environments). Table 3 reports the mean test accuracy for both the ESs. An excellent predictive performance is achieved for ES1, which is coherent with the results reported in [Gallicchio *et al.*, 2011]. Such an outcome is noteworthy, as the performance measurements in [Gallicchio *et al.*, 2011] have been obtained in a much simpler experimental setup, comprising RSS measurements from a single pair of rooms (that differ from those considered in this study). This seems to indicate that the LI-ESN approach, on the one hand, scales well as the number of training environments increases while, on the other hand, it is robust to changes to the training room configurations. Note that RSS trajectories for different rooms are, typically, consistently different and, as such, the addition of novel rooms strongly exercises the short-term memory of the reservoirs and their ability to encode complex dynamical signals (see RSS examples in Fig. 3).

ES 1	**ES** 2
$95.95\%(\pm 3.54)$	$89.52\%(\pm 4.48)$

Table 3: Mean test accuracy (and standard deviation) of LI-ESNs for the two ESs.

		LI-ESN Prediction	
		+1	**-1**
Actual	**+1**	$44.04\%(\pm 5.17)$	$7.88\%(\pm 5.17)$
	-1	$2.60\%(\pm 2.06)$	$45.48\%(\pm 2.06)$

Table 4: Mean confusion matrix (expressed in $\%$ over the number of samples) on the ES2 external test-set.

The result on the ES2 setting is more significative, as it shows a notable generalization performance for the LI-ESN model, that reaches a predictive accuracy close to 90% on the external test comprising unseen ambient configurations. Table 4 describes the confusion matrix of the external test-set in ES2, averaged over the reservoir guesses and expressed as percentages over the number of test samples. This allows appreciating the equilibrium of the predictive performance, that has comparable values for both classes. Note that total accuracy is obtained as the sum over the diagonal, while error is computed from the sum of the off-diagonal elements.

5 Conclusion

We have presented a RC approach to user movement prediction in indoor environments, based on RSS traces collected by low-cost WSN devices. We exploit the ability of LI-ESNs in capturing the temporal dynamics of slowly changing noisy RSS measurements to yield to very accurate predictions of the user spatial context. The performance of the proposed model has been tested on challenging real-world data comprising RSS information collected in real office environments.

We have shown that, with respect to the work in [Gallicchio *et al.*, 2011], the LI-ESN approach is capable of generalizing its predictive performance to training information related to multiple setups. More importantly, it can effectively generalize movement forecasting to previously unseen environments, as shown by the external test-set assessment. Such flexibility is of paramount importance for the development of practical smart-home solutions, as it allows to consistently reduce the installation and setup costs. For instance, we envisage a scenario in which an ESN-based localization system is trained off-line (e.g. in laboratory/factory) on RSS measurements captured on a (small) set of sample rooms. Then, the system is deployed and put into operation into its target environment, reducing the need of an expensive fine tuning phase.

In addition to accuracy and generalization, a successful context-forecasting technology has also to possess sufficient

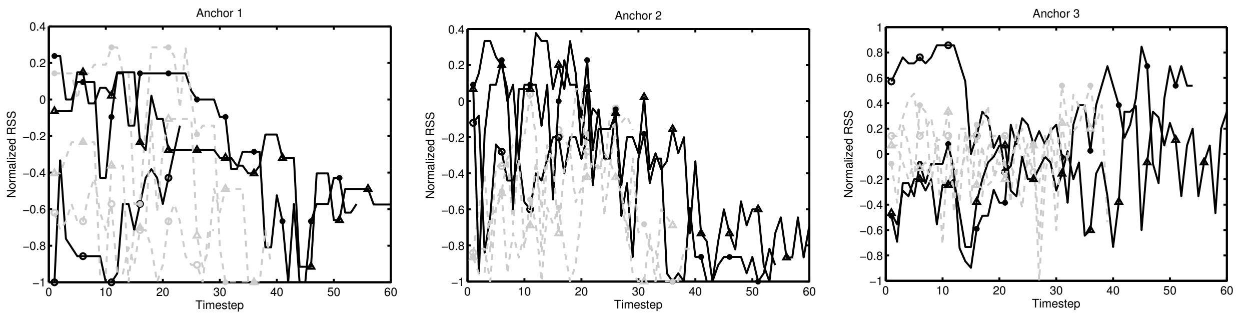

Figure 3: Examples of RSS sequences in the 3 datasets: trajectories leading to a room change are denoted as continuous lines, while dashed curves are examples from the negative class. Circles, stars and triangles denote sequences from dataset 1, 2 and 3, respectively. Due to space constraints, RSS streams are shown only for 3 out of 4 available anchors.

reactivity, so that predictions are delivered timely to the high-level control components. In this sense, ESN is a good candidate to optimize the trade-off between accuracy, generalization and computational requirements among machine learning models for sequential data. Such potential can be further exploited by developing a distributed system that embeds the ESN learning modules directly into the nodes of the wireless networks. By virtue of ESN's limited computational requirements, we envisage that such solution could be cost-effectively realized on WSNs comprising simple computationally constrained devices (e.g. see the objectives of the EU FP7 RUBICON project[3]).

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