ESANN 2016 proceedings, European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning. Bruges (Belgium), 27-29 April 2016, i6doc.com publ., ISBN 978-287587027-8. Available from http://www.i6doc.com/en/.

RSS-based Robot Localization in Critical Environments using Reservoir Computing

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Abstract. Supporting both accurate and reliable localization in critical environments is key to increasing the potential of logistic mobile robots. This paper presents a system for indoor robot localization based on Reservoir Computing from noisy radio signal strength index (RSSI) data generated by a network of sensors. The proposed approach is assessed under different conditions in a real-world hospital environment. Experimental results show that the resulting system represents a good trade-off between localization performance and deployment complexity, with the ability to recover from cases in which permanent changes in the environment affect its generalization performance.

1 Introduction

While being the subject of considerable research interest in the last decade, the problem of indoor localization is far from being solved. A number of recent international competitions on this topic [1, 2, 3] have shown a state of the art that is still heterogeneous, with solutions typically showing accuracy performance of about 1 m of average localization error in practical applications.

Robotics has produced specific techniques that can be used to localize mobile robots, e.g. based on cameras or laser range finders [4]. However, many of those techniques have still limitations such as the necessity to localize the robot on every start-up and reliability that is under the required level. For this reason, the robots currently employed across busy manufacturing plants and large hospitals still use localization approaches based on following painted lines or detecting magnetic landmarks that must be previously installed on the floor. The installation and maintenance costs, and the loss in flexibility - since these robots can only navigate on pre-programmed paths - pose a serious obstacle to a widespread use of logistic mobile robots.

*This work is partially supported by the EU FP7 RUBICON project (contract n. 269914). The authors would like to thank all the involved partners.

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In this paper we describe a system for indoor robot localization that exploits an easy to install and cheap wireless sensor network: radio signal strength index (RSSI) data are measured between a wireless device on a robot and a number of other devices (anchors) placed on the walls of the environment. Data is analyzed using Recurrent Neural Networks (RNNs), a class of learning models of consolidated use for the ability to capture dynamic knowledge from noisy streams of temporal data. In particular, within the Reservoir Computing (RC) [5] framework for RNN design, we take into consideration the Echo State Network (ESN) [6] model, a state of the art approach for efficiently learning in temporal domains. ESNs have proved to be particularly suitable for treating the noisy data gathered from sensor devices, enabling intelligent sensor networks and resulting in successful real-world applications in supervised computational tasks related to ambient assisted living and human activity recognition (e.g. [7]) as well as robot localization in realistic laboratory settings [8], as testified also by the recent success of the RUBICON project [9].

The proposed solution is experimentally assessed on a wing of a pediatric hospital. The results show the ability of our system to achieve a very good performance in real-world conditions and to recover (by learning) from permanent changes in the environment that could otherwise severely affect its operation and/or may require costly ad-hoc re-calibrations of the localization system.

2 Indoor Robot Localization in Hospital by RC

ESNs implement discrete-time dynamical systems, being composed of a N_R-dimensional recurrent non-linear *reservoir* that provides the system with a memory on the input history, and of a N_Y-dimensional linear feed-forward *readout* that computes the output. In this paper we use a variant of the standard ESN, called Leaky Integrator ESN (LI-ESN) [10], which has proved to be particularly suitable in dealing with the nature of input data originated from networks of sensors [7]. At each time step t the N_U-dimensional input $\mathbf{u}(t)$ is fed to the reservoir, which computes the state as $\mathbf{x}(t) = (1-a)\mathbf{x}(t-1) + a \tanh(\mathbf{W}_{in}\mathbf{u}(t) + \hat{\mathbf{W}}\mathbf{x}(t-1))$, where $\mathbf{W}_{in} \in \mathbb{R}^{N_R \times N_U}$ is the input-to-reservoir weight matrix, $\hat{\mathbf{W}} \in \mathbb{R}^{N_R \times N_R}$ is the recurrent reservoir weight matrix and $a \in [0, 1]$ is the leaking rate parameter. The output at time step t is computed by the readout as $\mathbf{y}(t) = \mathbf{W}_{out}\mathbf{x}(t)$, where $\mathbf{W}_{out} \in \mathbb{R}^{N_Y \times N_R}$ is the reservoir-to-readout weight matrix. The only trained component in the LI-ESN architecture is the readout, typically by means of pseudo-inversion or ridge regression. The parameters of the reservoir are left untrained after initialization under the constraint of the echo state property (ESP) [6]. In practical applications this results in a scaling of a randomly initialized $\hat{\mathbf{W}}$ such that the spectral radius ρ of matrix $(1-a)\mathbf{I} + a\hat{\mathbf{W}}$ satisfies $\rho < 1$. Further details on reservoir properties can be found in [11, 5].

The system described in this paper takes advantage of the synergy of two components: a primary (more costly) laser-based localization system and a secondary (cheaper) RC-based one. On the one hand, the RC-based system can be used as a diagnostic tool for the laser-based one, e.g. by detecting problems

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due to interactions with people that could interfere with the laser range sensors, and to re-initialize the primary location estimation whenever the robot must be restarted. On the other hand, the laser-based system can be used as a teacher for training the RC-based one whenever an update of the secondary localization system is required. In particular, we exploit this strategy to perform a re-training of the LI-ESN model in the case of permanent environmental changes.

A measurement campaign took place in a building of the Stella Maris pediatric hospital in Pisa, involving a wing with two corridors. As sketched in Fig.1, a small wireless sensor network (WSN) was installed, comprising 10 anchors placed on the walls at ≈ 1.5 m of height, on alternate sides of the corridors (one every ≈ 4.5 m), and a mote on the robot. RSSI data exchanged between the mote and the anchors was collected at 2 Hz while the robot moved back and forth along the corridors, following an indicative path shown in Fig.1. We considered

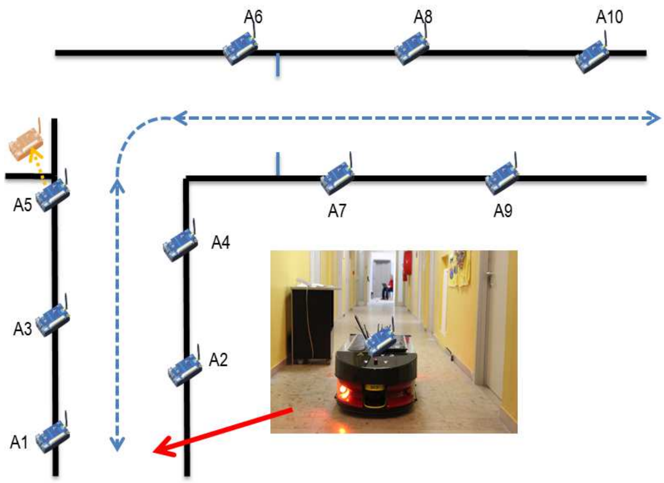

Fig. 1: A sketch of the considered hospital environment, WSN and robot path.

two experimental settings: a *normal operation setting* (NOS), corresponding to the full operational case, and an *environmental change setting* (ECS) in which a permanent modification to the environment affects the RSSI values and therefore presumably has a negative impact on the localization estimation provided by the RC system, thus representing an interesting case for the assessment of the recovery strategy based on re-training. To re-create these situations in a repeatable manner, the ECS setting has been implemented by moving anchor A5 behind the adjacent wall (see Fig.1), so that a section of the wall was in the line of sight between the anchor and the robot's mote. Note that, in particular, in this case the presence of the wall contributes to strongly increasing the noise in the RSSI signal between A5 and the robot mote. As a result of this perturbation, data coming from sensor A5 is considerably different between the NOS and the ECS cases. This aspect is even more relevant as anchor A5 is placed

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in a crucial position in the map, corresponding to the intersection between two corridors where the robot is required to turn, thereby making the ECS settings particularly challenging under the localization estimation point of view. In total we collected a *robot localization* dataset[1] containing 37 sequences pertaining to different experimental conditions, resulting in the definition of 2 regression tasks, in which at each time step the input is represented by the 10 RSSI signals and the target is the (X,Y) coordinates provided by the laser-based localization system on the robot. In particular, the NOS task contained 17 sequences, whereas the ECS task contained 20 sequences.

3 Experimental Results

For each task, the predictive performance of the RC localization system in terms of error in the Euclidean distance (ED) of the localization estimation provided by the LI-ESN, was evaluated on a separate external test set, comprising $\approx 25\%$ of the available data. We considered LI-ESNs with reservoir size $N_R \in \{10, 50, 100, 300, 500\}$, 10% of connectivity, leaky parameter $a \in \{0.1, 0.5, 1\}$, and with values in $\mathbf{W}_{in}$ and $\hat{\mathbf{W}}$ chosen within an alphabet of 16 values in the range $[-0.4, 0.4]$ (as in [7]). For each reservoir hyper-parametrization, 5 guesses were independently generated, and the results were averaged over such guesses. The readout was trained by pseudo-inversion and ridge regression with regularization parameter $\lambda_r \in \{10^{-4}, 10^{-3}, 10^{-2}, 10^{-1}, 5\ 10^{-1}, 1, 5, 10, 10^2, 10^3\}$. Reservoir hyper-parametrization and readout regularization were selected by a process of holdout model selection on a validation set ($\approx 25\%$ of the training set size).

A very good generalization performance is obtained by the RC system on the NOS task, indeed the mean test ED error achieved by the LI-ESNs on this task is 36.2 (± 4.8) cm. Note that, although the indicative path of the robot movements is given, the localization system is of general applicability, as it does not include any explicit knowledge about the details of the specific instance considered, e.g. the path followed or the robot speed.

	Validation	Test
LI-ESN before re-training	42.0($\pm$10.9)	208.8($\pm$50.6)
LI-ESN after re-training	78.8($\pm$5.4)	77.7($\pm$10.2)

Table 1: Mean ED error and std (in cm) achieved by LI-ESNs on validation (NOS/ECS task before/after re-training) and test sets of the ECS task.

The deterioration of the RC localization system due to environmental changes is assessed by evaluating the performance on the test set of the ECS task achieved by the LI-ESNs trained and selected on the NOS task. The effectiveness of the subsequent re-training process is then assessed by evaluating the performance obtained by LI-ESNs on the ECS task, running a model selection procedure analogous to the NOS case. Tab.1 reports the performance achieved by the

[1] The dataset is available at http://fp7rubicon.eu/uploads/HospitalWSN/robot_loc_SM.zip.

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RC system on the ECS task before and after re-training. As it can be seen, the mean test ED error obtained by the RC system before re-training is 208.8($\pm$50.6) cm, whereas after re-calibration, the mean test ED error is 77.7($\pm$10.2) cm, which represents a very good value also considering the specific difficulties that characterize the ECS conditions. The effectiveness of the re-training strategy

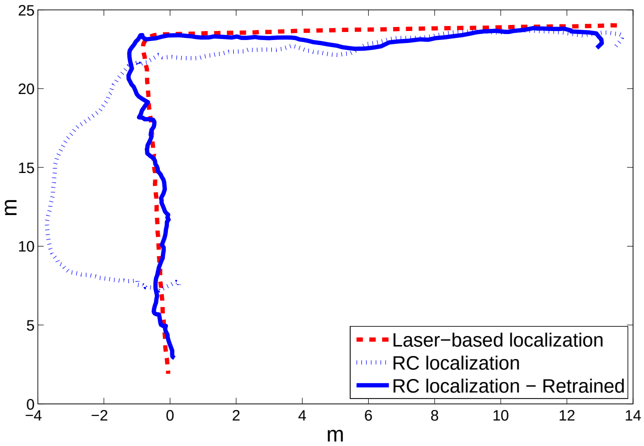

Fig. 2: Reference laser-based and RC estimated localization before and after re-calibration for a test trajectory under ECS conditions.

is also shown in Fig.2, which compares the target laser-based localization with the estimation provided by the RC system before and after the re-training on a test sequence of the ECS task. As can be seen, the localization estimation before retraining is mostly perturbed in a part of the robot trajectory that is close to the perturbed sensor, whereas the estimation provided by the re-trained RC system is much closer to the reference laser-based localization.

4 Conclusions

In this paper we have presented a system for indoor robot localization, exploiting the ability of RC to efficiently learn from noisy RSSI data generated by a WSN. The effectiveness of our approach has been assessed in a real-world hospital building, under different conditions. Results show a good performance in comparison to reference laser-based localization system, with a mean test error of 36.2 cm in normal operational conditions, which compares well with typical literature results (although still heterogeneous to have a clear reference) with localization errors roughly close to 1 m. Experimental results also showed the ability of our system to recover from permanent changes in the environment by a re-training strategy. In the considered real-world scenario, such strategy allowed the restoration a good localization performance also in the case of a severely compromising

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environmental modification, with a performance improvement that can be quantified in a reduction of the test error from more than 2 m (before re-training) to 77.7 cm (after re-training).

The proposed system represents an advantageous trade-off between performance and complexity of installation, maintenance and re-calibration. In particular, the use of learning allows the system to be flexible and easily re-adapted after environment perturbations, avoiding the need to start from scratch the costly design of pre-programmed rigid localization systems. The general applicability of the learning approach also allows us to envisage the integration with other sensor inputs, e.g. wifi network RSSI, GSM RSSI or IMU magnetometers, thus further increasing reliability and accuracy. Moreover, the proposed system allows a fruitful co-operation of laser-based and RC-based localization systems for diagnostic and training purposes. Overall, the robustness of the resulting system would eliminate the requirement for modifications to the environment (e.g. to install magnetic landmarks) and reduces the need for pre-programming robot tasks, thus ultimately leading to fleets of logistic mobile robots that are more flexible and cheaper to install and operate.

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