XXVII Brazilian Congress in Biomedical Engineering

October 26-30 2020 Vitoria (Brazil)

CBEB2020

XXVII Congresso Brasileiro de Engenharia Biomédica

Preface

For this edition of the Brazilian Conference on Biomedical Engineering (CBEB2020 – Congresso Brasileiro de Engenharia Biomédica), 665 papers were submitted, composed of 564 scientific articles (4-6 pages) and 101 Scientific Communications (Abstracts up to 2 pages). After the first round of reviews, 595 papers were accepted (514 full papers and 81 scientific communication). These 595 articles underwent a second review round, and at the end 551 papers (478 full papers and 73 scientific papers) were accepted to be presented at CBEB2020.

CBEB is promoted by the Brazilian Society of Biomedical Engineering (SBEB), with biannual periodicity, organized by researchers linked to a local research institution, with the collaboration of the entire scientific community linked to the area of Biomedical Engineering in Brazil. CBEB2020 was held on October 26-30, 2020 in Vitória (Brazil) and was organized in the following tracks:

- Clinical Engineering and Health Technology Assessment
- Biomaterials
- Tissue Engineering and Artificial Organs
- Bioengineering
- Biomedical Devices and Instrumentation
- Biomechanics and Rehabilitation
- Neuroengineering
- Biomedical Signal and Image Processing
- Biomedical Robotics, Assistive Technologies, and Health Informatics
- Biomedical Optics and Systems and Technologies for Therapy and Diagnosis
- Basic Industrial Technology in Health
- Special Topics

We would like to thank the sponsors CNPq and FAPES for making it possible to celebrate this event in times of uncertainty due to the COVID-19 pandemics.

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Dual Neural Network Approach for Virtual Sensor at Indoor Positioning System

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Abstract— **Individuals, with mental or physical disabilities, need that others know their localization within an indoor environment in order to receive adequate healthcare. This paper presents an indoor positioning system based on a received signal strength indicator (RSSI) sensor network, where positions are determined by an artificial neural network (ANN) from the received signals. This work investigates the effect of using the past and present data from the other sensors to estimate one missing signal, using a second ANN, and using it as a virtual sensor in the main ANN. For the study, a database was built in a typical residential environment with one transmitter and four receivers. The research studies the effect on the performance caused by the failure of one sensor showing the gains of using virtual signals, as well as a comparison of this virtual data with the measured data. The ANNs are trained with the cross-validation method to avoid overfitting. The selected number of neurons in the inner layer, for each case, was the complexity capable of presenting at least the same performance of an oversized ANN, which was also trained without overfitting. The system developed achieved a considerable efficiency, being able to reproduce the position of the individual with less than 0.36 m of average error when all four receivers were working properly. However, this average error can increase to 0.52-0.91 m when a receiver is at failure, depending on which one fails. Nevertheless, the use of the proposed virtual sensor can diminish about 0.2 m of average error in case of failure. Therefore, the use of virtual data proved to be a feature capable of improving positioning when a sensor fails, in relation to the alternative of performing this positioning without this sensor nor its corresponding virtual signal.**

Keywords— **Neural Networks · machine learning · indoor localization · wireless sensor network · virtual sensor.**

I. INTRODUCTION

Localization technology inside an indoor environment may be of interest for many of reasons such as informing healthcare staff of the position of their patients [1] or to analyze how different people behaves during building evacuation procedures [2]. Some organizations get interest in these technologies in order to track their clients or to maintain a complete computational environment at factories [3]. Global Navigation Satellite Systems (GNSS) signals are not proper for indoor detection and consume too much energy [4]. Thus, wireless sensor network (WSN) that identify the Received Signal Strength Indicator (RSSI) became a popular solution [5] [6]. Although there are other algorithms, such as time of arrival (TOA) [7], the RSSI approach presents advantages like lower cost and dismissal of additional hardware [8].

A use of smartphones for indoor localization was proposed by [9], who fused information from a Pedestrian Dead Reckoning (PDR) system with the RSSI data obtained through the Wi-Fi signal, compass, accelerometer and gyroscope of the phones.

A study comparing three techniques (with Bluetooth, Wi-Fi and ZigBee) for indoor positioning systems was produced by [10]. Their indoor positioning system (IPS) had fixed anchor and mobile nodes spread through a hospital. Although image processing with Wi-Fi presented more accuracy, it had the greatest cost. Another of these techniques mapped the room through Bluetooth, however it was severely impaired when a sensor presented failure. Thus, it may be beneficial to develop virtual sensors, which activates upon failures detection of a number of the sensors, and provide information based on present data from still functioning sensors and past recorded data. This is possible through machine learning methods as show by [11], which applied an Artificial Neural Network (ANN) and data-mining techniques to develop a virtual sensor to effectively acquire cylinder pressure.

The present paper shows a method based on ANNs for estimating the position of a target with signals from four RSSI sensors in four different locations with a main feed-forward ANN. In case of sensors fault, it is possible to continue determining the position of the target with an alternative ANN, though with less precision. In order to reduce the loss of precision a second ANN estimates the data from the faulting sensor based on past and current data from the other RSSI sensors. Then the calculated signals are used as input to the main ANN. The database recorded for this work consists of a set of positions and its correspondent Bluetooth RSSI data gathered with android based smart phones.

II. RELATED WORKS

ANNs have their origin in the artificial neuron described in [12]. This neuron was used to compose a network, called Perceptron [13], with only one layer of binary neurons. The delta rule, presented by [14], based on the error square minimization, was a remarkable evolution, allowing the efficient training of this Perceptron, with real domain outputs.

To solve more complex logical problems, perform nonlinear discrimination or approximate nonlinear functions, the backpropagation algorithm was introduced by [15], which can calculate the internal layer errors. These Multi-layer Perceptron (MLP) networks, according to the universal approximation theorem [16] are able to approximate any function exactly with a single inner layer and with 2n + 1 artificial neurons where n is the number of entries. Another theorem by [17], stated that a ANN with a single hidden layer can approximate any measurable relationship r: Rn− > Rm, where m is the number of outputs, with its accuracy depending on the number of neurons in the hidden layer. The cross validation approach [18] is commonly used to avoid overfitting. This technique divides the original samples in three sets: training, validation and verification. The first set is successively submitted (each in a training cycle or epoch) to the ANN within the training phase. Thus, the algorithm continuously evaluates its own performance through sum of the square of errors at each epoch, with the validation samples. The detection of signs of the start of the overfitting phenomenon, stops the training phase. Finally, the ANN is applied to the verification samples that were not used previously in training or in the definition of the neural network complexity to test its generalization capability [18].

The system developed by [19] locates smartphones combining information from Wi-Fi and GNSS signals through paths with transitions between indoor and outdoor environments. A combination of a RSSI with pulse sensors in the writs of the patients has been presented by [20].The inclusion of light sensor and map information almost doubled the precision in comparison to inertial sensor approaches [21]. A low cost alternative has been proposed by [22] that implemented an IPS with RSSI from Bluetooth of a WSN composed Android mobile devices, also to an IPS by [23], who joined this data with magnetic field sensors (MFS) information and images interpreted by a deep learning application.

Machine learning techniques also have been applied for IPS by [4], who investigated least-squares SVM, support vector regression and vector output regularized least squares with RSSI fingerprinting. Another application of machine learning in IPS was proposed by [24], whose MLP reduced noises in an IPS. A statistical method enhanced the results of [25] by correcting RSSI measure errors. A study of filtering functions improved the accuracy of a Bluetooth RSSI. Low Energy has been used by [26], achieving an accuracy of less than 1.5 meters in 80 percent of the times it has been used. A fingerprinting mapping using RSSI online *k*-nearest-neighbor algorithm for Wi-Fi indoor services was developed by [27], while [28] used a feature adaptive online sequential Extreme Learning Machine to lifelong Wi-Fi indoor localization technique. Also, a fusion of video camera and radar sensors through a convolutional neural network was studied by [29].

This research aimed to fill the gap, observed in the works previously described, with respect to the occurrence of failures in part of the sensors, which can impair the functioning of the system. To this end, an IPS with an ANN is developed that compensates for sensor failures by emulating its results based on information from other sensors.

III. Methodology

A. Database Construction

The database for this research was built with the help of five Android devices: one of these served as the Bluetooth emitting mobile node, while the other four were fixed along the scenario, thus becoming anchor nodes. The scenario consisted of a typical 75.3 m^2 apartment, in which paths were chosen for analysis, considering the furniture disposition, as shows Figure 1. A series of points were marked along these paths, 0.4 m apart from each other. For each of these points the anchor nodes collected multiple RSSI data within a period of two minutes. These nodes, labelled S_1, S_2, S_3 and S_4, were positioned at this map. Sensor S_1 was positioned at the northwest of the dinner room, while the sensor S_2 is at the southwest corner of the living room. Sensor S_3 is at the south entrance of the corridor and sensor S_4 is at the northwest corner of the kitchen. The collected data were sent to a computer for further analysis in the MATLAB® software to determine mean value, median, standard deviation and maximum and minimum values, which were important to devise a proper ANN.

Three paths provided data for neural network training sampling. The first path comprises the way between the entrance door (the top point of the hall in the map) and the living room passing by the point S_2. The second path starts at the entrance door and ends at the laundry room. The third path goes from the entrance door to the bathroom, and from the bathroom interior to the bedroom center passing through the corridor. Another three paths provided data for the verification of the performance obtained with the methodology used and for verifying the generalizability of the ANN. The fourth path is the course from the laundry room to the living room passing by the sensor S_2. The fifth path is the route from the living room passing by the sensor S_2 to the bedroom. The sixth path is the course from the interior of the bedroom to the interior of the bathroom. The points forming each path have been measured in terms of X and Y plane.

B. System Architecture and Experiments Setup

The target node emits a Bluetooth signal that is perceived by the anchor nodes (S_1, S_2, S_3 and S_4), which detect the RSSI of the target. The nearer the target is of the anchor, the greater the RSSI is, though this relation is nonlinear. The distances between a target and a sensor could be determined by a Euclidean distance calculation, and the coordinates calculated geometrically from these distances. However, in this work an ANN has been used directly the RSSI to better address the non-linearity of these signals. This ANN has 20 inputs formed by the data from up to five last points recorded by each of the four sensors, thus an auto regression AR5. There is two outputs for this ANN: one for the measure of the target according to the X-axis of the Cartesian plane and one for the position along the Y-axis. If the system detect that one of the data streams of the sensors is missing, it requests the correspondent data from a virtual sensor. This virtual data comes from a second ANN, which has been previously trained with the data from the other three sensors. Therefore, this ANN has generated virtual data in the case of failure on any of the four receivers. This ANN has been designed with 15 input neurons, considering the past and present five positions of each of the three remaining anchor nodes. The ANN output layer has one neuron as the network aims to generate just one RSSI signal. Figure 2 presents a flow chart of the system architecture. A study has been developed to determine the best number of neurons for the inner layers of both ANNs, considering this number is the one that results in an ANN at least equivalent in performance to more complex networks. Once the ANNs are trained to take profit of the resulting information of walks through the path, samples of different directions are considered as different paths. So, the training paths are applied in both directions. Besides, the data from paths 1, 2 and 3 are divided in two parts, by alternate selection, for the validation and verification. After the data from the paths were ordinate sequentially, this method separated only the ordering multiple of three, for the selection of the validation registers to result in a more representative training series. That procedure resulted in 99 registers for the training algorithms and 49 validation algorithms necessary for the cross validation technique. The verification paths were considered in just one direction and, therefore, consist of 75 registers. The paths area also drawn in Figure 1.

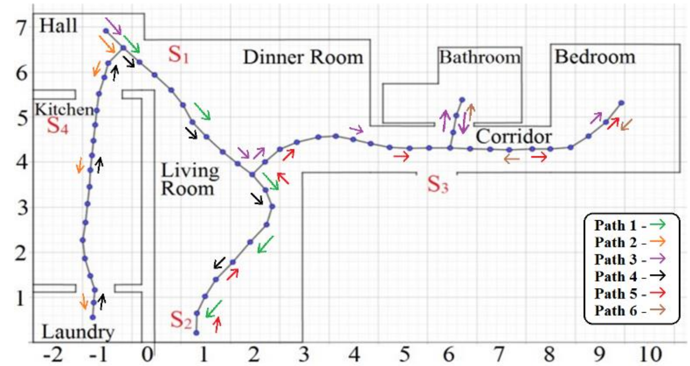

Fig. 1 Map of the 75.3 m^2 apartment, sensors (S_1, S_2, S_3 and S_4) and measured points.

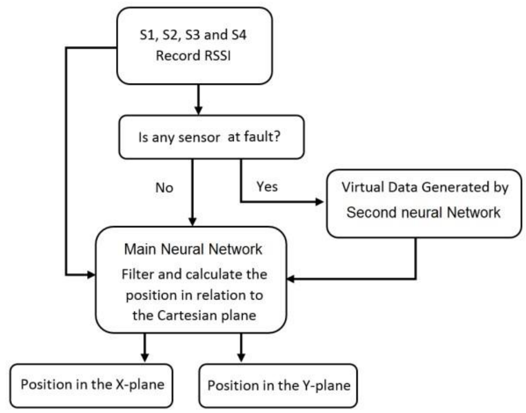

Fig. 2 Proposed system architecture.

The proposed methodology is evaluated comparing the positions found by the ANNs with the recorded point positions. The parameters used for the evaluation of the proposed methodology effectiveness are the average errors in respect to the position measured according to the X and to the Y axis. The average distance error verifies the Euclidean distance between the real point and the calculated by the ANN. The Nash coefficients evaluate the proportion of the variance of the data explained by the model.

IV. Results

The performance of both ANNs are evaluated by the sum of the square errors, the Nash coefficient and the absolute average error between the observed and calculated data. The Nash efficiency coefficient represents the proportion of the variance explained by the model. This parameter varies from the negative infinite to 1. The better the model, the closer the Nash coefficient will be to one. Figure 3 presents the sum of the square errors by the number of neurons at the hidden layer for the complexity research of the main ANN.

It was possible to infer that the performance of the system with 5 neurons was better in relation to oversized networks. The test also verified that the performances of too simple networks are impaired by their lack of degrees of freedom. The ANN of all virtual sensors performed better with five neurons for the hidden layer.

This section presents the results of this research. Figure 4 presents the graphs comparing the results of each of the virtual sensors generated by the second ANN to the signals it reproduces. These graphs include the reproduction by all virtual sensors of the verification paths (4, 5 and 6). The virtual sensors that substitute the sensors S_1, S_2, S_3 and S_4 are represented in this work as VS_1, VS_2, VS_3 and VS_4.

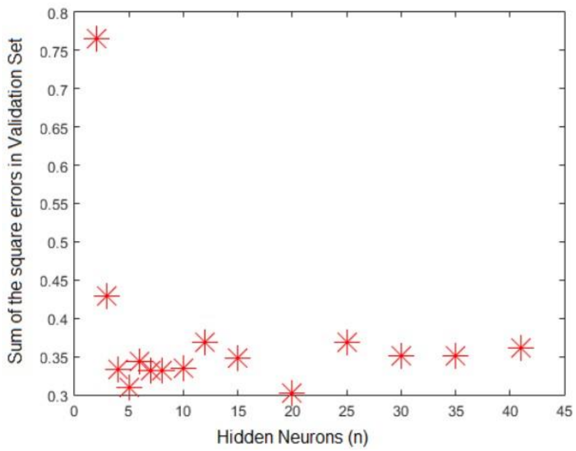

Fig. 3 Evaluation of the square errors sum.

Table 1 shows the average errors in respect to the axis X and Y (26.2 cm and 24.1 cm), besides the average distance error (35.5985 cm) of the proposed ANN alimented by data from all four sensor nodes in relation to the observed. The table also displays the Nash coefficients (0.987 and 0.950) for this configuration in respect to X and Y planes.

Table 2 has a similar purpose of Table 1 as it presents the values of the average errors and Nash efficiency coefficients in respect to the X and Y axis, besides the average distance error. Table 2 shows this statistic data for the ANN when the system operates with just three of its sensors.

Table 3 has an analogous purpose to Table 2, displaying the behavior of the ANN. However, Table 3 shows the evaluation of this criteria (error statics in respect to X and Y axis and in respect to the distance) when the ANN receives the virtual sensor data besides the other three sensor data.

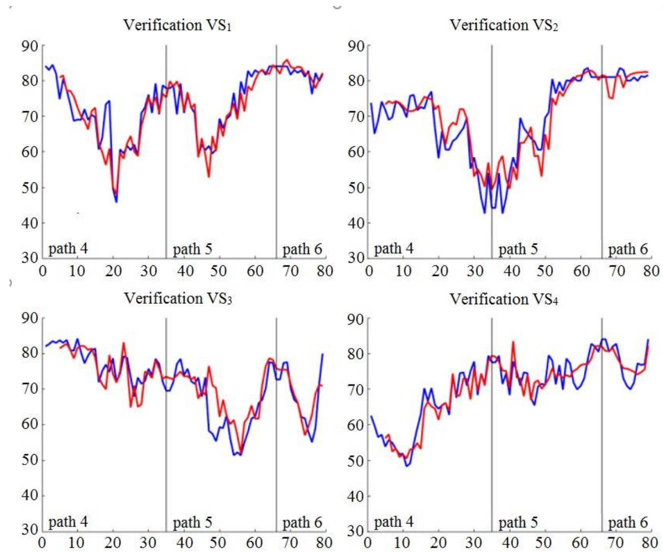

Fig. 4 Virtual sensors signal verification compared to their correspondent sensor signal.

Table 1 Errors and Nash coefficients when the four sensors are active.

Parameters	Parameters Values
Average X Error (cm)	26.2
Nash in X	0.987
Average Y Error (cm)	24.1
Nash in Y	0.950
Average Distance Error (cm)	35.5985

In order to have another view and to understand how well the ANN with the four sensors works and with one of these sensors substituted by virtual sensors, the charts of the verification of the ANNs are presented in Figure 5 and in Figure 6. Figure 5 presents XY plots of the behavior of the ANN with all four combinations of three real sensor and one virtual sensor tracking path 5. Analogously, Figure 6 presents graphs of the ANN tracking path 4 and path 6.

Table 2 Errors and Nash coefficients per set of three active sensors.

Parameters	$S_1S_2S_3$	$S_1S_2S_4$	$S_1S_3S_4$	$S_2S_3S_4$
Average X Error (cm)	58.4	40.6	71.3	55.0
Nash in X	0.95	0.97	0.92	0.95
Average Y Error (cm)	39.4	33.0	57.2	29.4
Nash in Y	0.88	0.91	0.75	0.93
Average Distance Error (cm)	70.45	52.32	91.40	62.37

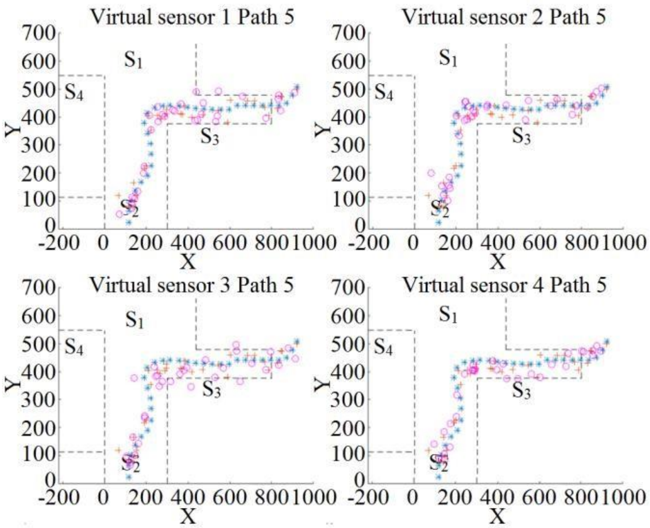

Fig. 5 Verification with path 5. '*' path is the real route, '+' path is traced by the 4 sensors ANN, 'o' path is traced by the ANN with a virtual sensor.

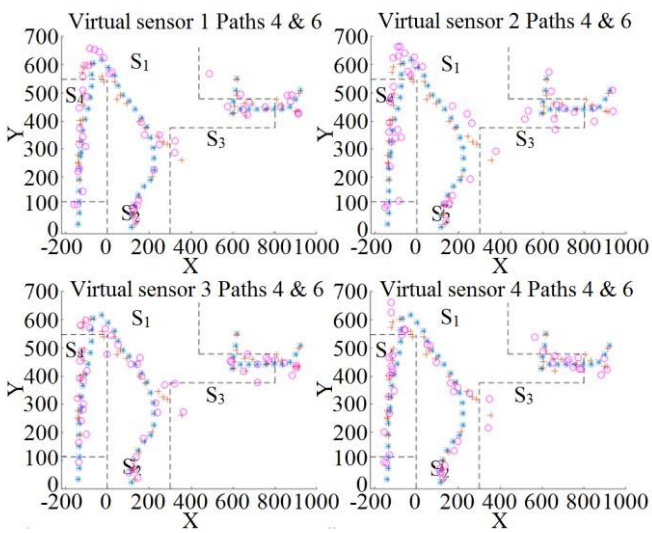

Fig. 6 Verification with paths 4 and 6. '*' path is the real route, '+' path is traced by 4 sensors ANN, 'o' path is traced by virtual sensor ANN.

V. Discussion

In Figure 4 it is remarkable that the second ANN is reproducing the collected data and, thus, building its virtual sensors. However, the accuracy of this reproduction has a certain variation between each virtual sensor. It is noteworthy that the virtual data signal VS_1 shown an overall great accuracy. VS_3 and VS_4 fared well especially in reproducing path 4, while the reproduction of VS_2 had better results in path 5. Comparing Tables 1 and 2, it is perceivable the difference of using all four or just three sensors. Depending on the combination of three sensors used, the failure of a sensor aggregates distance error from 0.167 to 0.55 m to the position measure. This difference is due to the disposition of the four sensors, the walls and the furniture. The more sensors used as inputs, the better precision the ANN will have.

Table 3 Errors and Nash coefficients per set of three active sensors and a virtual sensor.

Parameters	$S_1S_2S_3 + VS_4$	$S_1S_2S_4 + VS_3$	$S_1S_3S_4 + VS_2$	$S_2S_3S_4 + VS_1$
Average X Error (cm)	38.60	44.2	60.3	49.8
Nash in X	0.975	0.968	0.935	0.951
Average Y Error (cm)	32.3	42.90	49.0	39.6
Nash in Y	0.926	0.863	0.757	0.880
Average Distance Error (cm)	50.33	61.60	85.28	70.43

A comparison between Tables 2 and 3 shows that in most cases the ANN fed also with the virtual sensor data has better results than the alternative ANN that receives only the data signals from the three remaining real sensors. VS_4 was the most successful virtual sensor in enhancing the main ANN performance as it diminished the average distance error in relation to the real position in 0.2 m, while VS_2, reduced this error by 0.062 m. According to table comparison, the use of the virtual sensors VS_1 and VS_3 did not presented advantages.

Analyzing the charts described in Figure 5, path 5 has been better tracked by the ANN with VS_4. This is likely due to this sensor being farther from this path. Thus, the closer sensors had already very reliable information. The ANN with the virtual sensor VS_2 tracked more precisely the real route at the corridor, being comparable to its behavior with 4 working sensors. Figure 6 has shown the effects of all four virtual sensors in the ANN tracking path 4 and path 6. Comparing these four charts, it is perceivable that virtual sensor VS_3 had difficulty tracking the path of the way between the bathroom and the bedroom, while the other virtual sensors fared considerably better. At this path, virtual sensor VS_2 shows less precision, but better accuracy than the other virtual sensors. At the path between the laundry and living rooms, it is noteworthy to point out that virtual sensors VS_1 and VS_3 fare very well tracing the route within the kitchen and living room. At the Hall, virtual sensors VS_1, VS_2 displayed more reliable results. VS_3 presented more accuracy at tracing at the dinner room. Nevertheless, both Figure 5 and Figure 6 show that the ANN tracked well the three paths at its verification stage both with four real sensors and with one virtual sensor complementing the information of the other three. However, sudden changes of direction cause greater errors, especially for virtual sensors, as noted in the passage through the hall on path 2. In this region, VS_3 resulted in fewer errors.

VI. CONCLUSIONS

Individuals, with mental or physical disabilities, need others to know their localization within an indoor environment to receive adequate healthcare. This paper presents an indoor positioning system based on a received signal strength indicator (RSSI) sensor network, where positions are determined by an artificial neural network (ANN). This work investigates the effect of using the past and present data from the other sensors to estimate one missing signal, using a second ANN, and using it as a virtual sensor in the main ANN.

A comparison of the final results, with the alternative of using a different ANN with only three sensors, was developed. Once the ANN are excellent function approximators, this models obtained good results, in some cases being comparable to model that used a virtual sensor. The virtual sensor method revealed itself as an important alternative to improve the main ANN calculation of the coordinates, even when one of the sensors fails. The virtual sensor was favored by the faithful reproduction of the data signals of each missing sensor by the ANN. It is expected that the installation of more sensors would result in localization with even more accuracy by the ANN, what may be theme for further studies.

ACKNOWLEDGMENT

We are thankful to Coordination of Improvement of Higher Education Personnel (CAPES) for the financial support.

CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

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