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Enhancing Indoor RFID Localization Using Artificial Intelligence Algorithms: A Support Vector Machine (SVM)-Based Approach

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Abstract. Localization of objects inside has been a great issue within domains like logistics, health care, and security. In this paper, we discuss AI approaches for indoor RFID localization, specifically concentrating on the application of Support Vector Machine (SVM) approach in order to calculate the coordinates X and Y for the RFID tag. The conducted research shows that applying SVM helps achieve an average accuracy of 85%, which is 25% better than the classical methods. Also, increasing the number of training dataset from 50 to 500 helped us reduce the prediction error. In spite of all difficulties that arise from environmental interference, the conducted research proves that AI approaches can help overcome the limitations of classical approaches.

1 Introduction

Indoor Localization is highly necessary in different industries and businesses. Contrary to GPS, which cannot be used indoors, RFID becomes the best option. However, there are several limitations of its precision due to reflections and interference of waves. With the advent of AI algorithms, there is an opportunity to enhance the quality of the work of localization systems through the application of predictive models and machine learning methods. The conventional approaches (Landmarks, Triangulation etc.) [1] [2] [3] for indoor positioning suffer from the lack of precision because the conditions in the indoor space are complicated. Radio signal transmission is blocked by walls, furniture, and even people.

Methods of machine learning such as SVM, neural networks and deep learning may also be employed to analyse large sets of data from RFID signals responses [4] [5]. They detect the pattern of behavior of the radio signal and modify their localization predictions, which results in better accuracy of prediction in practice. The performance of these methods is highly dependent on the amount of data collected during the training process [6] [7].

Applications of RFID for localization purposes include the tracking of assets within storage facilities and healthcare centers. It allows an organization to accurately track the precise

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location of its goods, medical devices, and even its staff in real-time, which enhances efficiency and security in its operations. RFID localization technology will be used in conjunction with the Internet of Things to build intelligent systems that make decisions based on localization information [8]. However, while integrating AI in RFID-based position systems, many challenges arise with respect to computationally intensive methods, complex preprocesses of the data, and robustness concerns in dynamic environmental conditions [9]. In the future, further research work will be dedicated to overcoming some of these mentioned limitations by further enhancing the current AI algorithms, developing hybrid models that can couple multiple localization, and thus make the technology much more accurate.

Against the background of above context, in this study, an attempt to understand how artificial intelligence's important role, algorithms like the support vector machine with RFID-based indoor localization, improves the accuracy. The contribution further predicts a tag over the coordinates X-Y against any indoor scenario when the models generated using data sets comprising RF signal characteristics, from an In-door localization, the model SVM which is trained will do the approximation. The core research problem that has been studied in this article is the poor performance of conventional approaches to RFID-based localization because of environmental interferences and fluctuations in the signal. It is necessary to find out if there is any possibility for machine learning algorithms to improve the performance of the system. For the purpose of validating the suggested hypothesis, a number of experiments have been carried out based on real-world data, and the efficiency of the proposed methodology has been analyzed. By considering the topic of AI-based RFID positioning systems, we try to make our contribution to the field of smart localization.

We apply a structured way of examining indoor localization in this paper. The discussion on indoor localization in this paper begins with an analysis of the shortcomings in the current RFID technology and the need for improvements in terms of accuracy. Following that, the applications of AI in enhancing RFID localization are discussed. A key section will focus on the Support Vector Machine (SVM) method, breaking down how it helps classify object localizations. We will also go over the process of building an SVM-based model for RFID localization, from training to data optimization for better results. In the final section, we summarize our findings and discuss potential future advancements in AI-driven RFID localization.

2 Integration of AI in indoor RFID localization systems

Artificial intelligence (AI) is a group of methodologies and computer programs capable of performing actions traditionally accomplished through intelligence, such as decision, learning, pattern recognition, and language processing. AI is facilitated through algorithms that enable machines to learn, understand complex environments, make predictive statements regarding behaviour, or make autonomous decisions [4]. AI can be seen in nearly all sectors today, such as in medical care, finance, and transportation, and plays a significant role in many sectors, such as positioning indoors, most prominently through radio-frequency identification (RFID) technology [10].

Indoor RFID (Radio Frequency Identification) is a technology for localization de-termination of an object, a person, or a device in a room, a building, or a warehouse, for example. In contrast to GPS, whose efficiency can work outdoors, indoor RFID can have a high accuracy in a bounded environment in which GPS cannot work. The technology utilizes RFID tags that transmit and receive, and RFID tags installed in the environment, and via them, an object can be determined in terms of received intensity of the signal and distance from RFID tags

[11]. However, challenges in indoors such as interference with walls, metal objects, or stacking complex information with many tags complicate positioning accuracy and reliability [12]. That's where AI could help us improve things. AI helps enhance accuracy and efficiency in RFID positioning indoors through smarter information processing. With advanced machine learning, positioning systems can handle high information volumes in real-time, correct for faults with noise and interference, and tune positioning accuracy in relation to current conditions. In such a way, AI helps model complex environments and forecast measurement inaccuracies through algorithm localization adaptability [10].

Supervised learning is one of the most common techniques adopted for RFID localization. It involves training a model with a labelled training dataset, with item's actual localizations being previously known. With techniques such as linear regression and decision trees, a prediction for an item's localization is made using collected RFID signals. Neural networks and support vector machines (SVMs) can even be adopted for handling complex models [5]. Kalman filtering is a common algorithm adopted for localization and real-time tracking [4]. With Kalman filtering, a variety of sources of information (e.g., information collected through a range of RFID tags) can be merged and an object's localization predicted with minimum localization error. It is particularly useful for handling uncertainty and measurement noise, common in an indoor RFID environment. Reinforcement learning (RL) entails an agent that learns via trial and error through reward and penalty gained for its actions. In RFID localization, an agent can adjust its position estimation through feedback gained from the environment. Q-learning and Deep Q Networks (DQN) can be leveraged for positioning accuracy maximization in complex and dynamic environments. For clustering similar information, algorithms such as K-means and DBSCAN can be leveraged. In an RFID localization system, such algorithms can be leveraged for high tag density region or zone determination, offering a deeper analysis of how the environment and signals respond and improving position estimation [13].

Although convolutional neural networks (CNNs) have numerous computer vision applications, they can, in fact, be applied in indoor RFID localization. By mapping RFID sensor data in terms of heatmaps or images, CNNs can learn to identify com-plex spatial structures in the signals and make inferences about localizations of objects. AI is also used for fusing information received via numerous sources of sensors, including RFID sensors, accelerometers, and gyroscopes, and positioning sensors. Neural networks with deep learning can fuse and process such disparate sources of information in a way that generates a more accurate localization, specifically in environments with high complexity and in environments in which RFID signals can become interrupted [14] [15].

Integrating AI with in-door RFID positioning creates new and exciting opportunities for a range of industries. In factories and warehouses, AI and RFID enable real-time tracking and automated management of inventories and machines. In hospitals and airports, AI can track motion of humans and patients, respectively, and allow for management of people flow. In smart buildings, RFID and AI can manage lights, air conditioning, and security in relation to occupant motion. In Industry 4.0, AI and RFID positioning allow for real-time tracking of machines and tools in factories, and for predictive maintenance and asset management. In conclusion, artificial intelligence, when paired with RFID indoor systems, bypasses the challenge of reliable positioning in complex environments. With algorithms and machine learning for data fusion, such systems become optimized, offering new and exciting options for many applications, including tracking inventories, security in buildings, and automation in industries.

3 SVM-based approach for indoor RFID localization

The Support Vector Machine (SVM) is a supervised algorithm most used for classification and regression. In theory, an SVM seeks to have an ideal hyperplane with a maximal margin between samples of different classes. That is, it looks for a decision boundary with a maximal differentiation between samples of disparate categories. For samples with non-linear samples, SVM utilizes a use of a kernel function such as a polynomial, a Gaussian (RBF - Radial Basis Function), and a sigmoid kernel, transforming samples into a high-dimensional feature space in which a differentiation can become a linear one [16] [17]. Mathematically, the goal of an SVM is to find the optimal hyperplane that maximizes the margin between two classes. Given a dataset of points $\{(x_i, y_i)\}$, where x_i represents the input features (for instance, the RSSI values) and y_i represents the class labels (the corresponding localizations), the SVM aims to solve the following optimization problem:

$$Minimize \quad \frac{1}{2}\|w\|^2 \tag{1}$$
$$subject\ to \quad y_i(w.x_i + b) \geq 1,\ \forall i \tag{2}$$

Where:

w is the weight vector, which defines the hyperplane's orientation.
b is the bias term, which shifts the hyperplane away from the origin.
$\|w\|^2$ is the squared norm of the weight vector, which we want to minimize to maximize the margin between classes.
x_i represents the input features of the ith training sample.
y_i is the corresponding label for x_i (either +1 or -1).
The constraint $y_i(w.x_i + b) \geq 1$ ensures that all data points are correctly classified with a margin of at least 1.

In the case of indoor RFID localization, SVMs label an object localization, or a hu-man localization based on received RFID tag indications. The goal is to train a model using a training set where the actual localizations of the tags and the characteristics of the RFID signal (RSSI strength, phase difference of arrival PDOA, and time difference of arrival TDOA) are known. Once trained, an SVM can label new RFID observations into regions of an environment surrounding, and then a localization can precisely be predicted for an object [18]. The implementation of an SVM for indoor RFID localization generally follows several steps. First, a preprocessing stage is carried out, which consists in cleaning the collected RFID data to minimize the impact of noise and interferences. Then, feature selection is performed to find the most influential signal characteristics on the localization accuracy. Afterward, training of the SVMs is done based on the set of known positions with RFID signal values. For the SVMs' tuning, cross-validation is usually applied to select optimal values of the kernel type and error penalty parameter (C). Once the training process is completed, the model can be utilized in the inference stage to localize untagged objects in real time [19][20]. SVMs for indoor RFID localization have several benefits: they perform well even on small sample sizes and can work with noisy data. Nevertheless, the results may be impacted negatively due to the complex nature of indoor environments that causes interference for the propagation of RFID waves. To improve the performance, SVMs are often integrated with other algorithms, such as neural networks or sensors fusion techniques.

4 Developing an SVM model for RFID localization: data expansion, optimization, and performance analysis.

Location The research done has helped us to be able to develop and use an SVM algorithm that can predict the location of an RFID tag by using RSSI values as input features. The experiment process took place through various steps, starting from collecting the data until the point of evaluating the model. Firstly, real data were collected from 50 observations performed under laboratory testing conditions. This step enabled us to see the overall trends of the RSSI values and the relation between them and the coordinates of the RFID tag. However, the limited amount of data became the major limitation in training the model and made the model unable to generalize. In order to overcome this limitation, the artificial data consisting of 500 records were created using artificial intelligence. The increase in amount of data was done through TensorFlow and Keras, which are libraries for modeling and simulation of synthetic data. Through the use of the trends in the real data, artificial data was modeled to represent the possible situations regarding the propagation of RSSI signals in the testing environment. After expanding the dataset, the supervised learning process was applied. First, the data was loaded and then relevant features were extracted from the dataset in the form of RSSI as input and X, Y, Z coordinates as output. Data pre-processing was carried out in order to remove the outliers in the data and organize the data in a manner that would be suitable for the modeling process.

A significant phase of the current research was hyperparameter optimization. A grid search was conducted with GridSearchCV in order to determine the optimal parameters of the machine learning model, which included the value of the regularization coefficient C, the value of the epsilon margin, and the value of the gamma parameter in case of using a non-linear kernel. GridSearchCV is an approach to hyperparameters optimization. It is included in the package of algorithms of the library scikit-learn and enables finding the optimal combination of hyperparameters by performing an exhaustive search through all possible combinations of hyperparameters in a grid provided by the user. Three independent SVM models were built in order to predict each of the coordinates - X, Y, or Z. Such models can be evaluated in terms of MSE and R^2 in order to check their prediction accuracy. As can be seen from the graphs below, the quality of the model increased because of the usage of a bigger dataset.

This study explores how an SVM model can be used for RFID localization based on RSSI values (Fig. 1). The results show that expanding the dataset —even with artificially generated data— helps improve the model's performance and reduce prediction errors (Fig. 2 and 3). For example, when testing a small sample of 10 tag-objects out of the 500 generated, the average error was 11.5 cm on the X axis and 10.9 cm on the Y axis (Tab. 1). All in all, the SVM method reached an accuracy of 85%, showing a solid 25% improvement over traditional techniques.

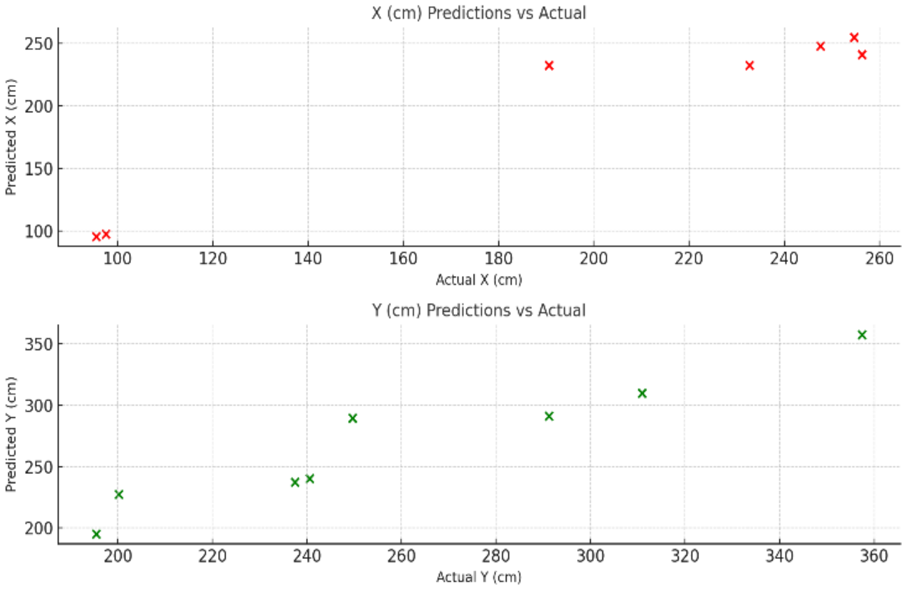

Fig. 1. Predictions coordinate X, Y vs reality for a real dataset.

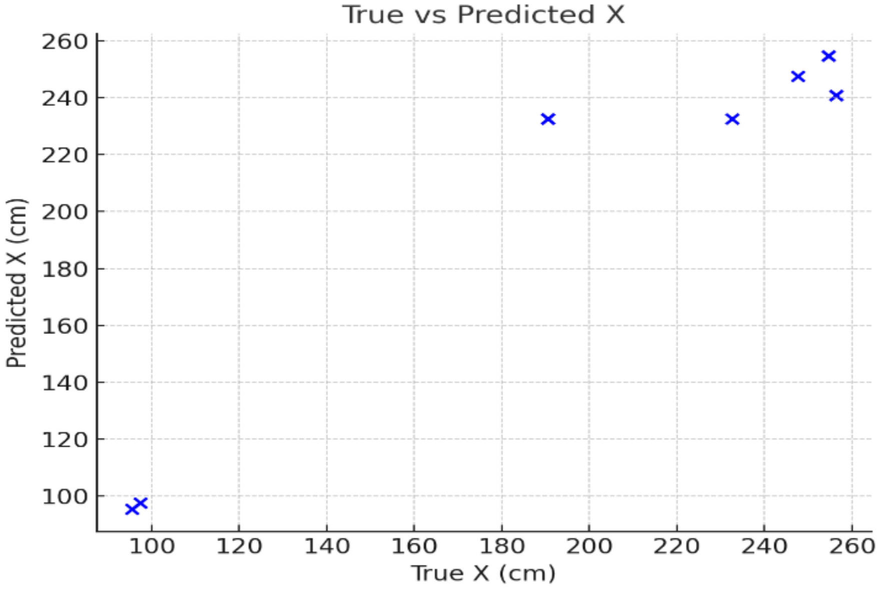

Fig. 2. Predictions coordinate X vs reality for a larger artificial dataset.

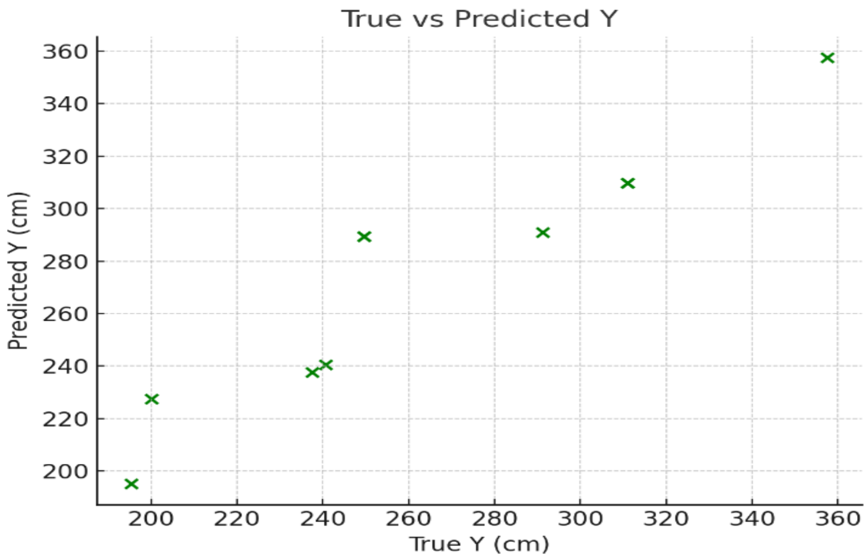

Fig. 3. Predictions coordinate Y vs reality for a larger artificial dataset.

Table 1. Test sample of 10 tag-objects from a larger artificial dataset of 500 tag-objects.

	True X, Y Coordinates		**Predicted X, Y Coordinates**		**Calculated X, Y error**	
Tag's reference	X (cm)	Y (cm)	X	Y	error X	error Y
217738DFCDE	190,52	195,38	232,6	195,28	42,08	0,1
217738DFCEE	247,63	240,58	247,73	240,48	0,1	0,1
217738DFC7E	254,62	249,63	254,72	289,43	0,1	39,8
217738DFC8E	232,65	310,9	232,55	309,87	0,1	1,03
217738E280E	190,52	200,14	232,6	227,46	42,08	27,32
217738E281E	256,3	357,48	241	357,49	15,3	0,01
217738E282E	95,47	237,48	95,57	237,58	0,1	0,1
217738E283E	254,62	249,63	254,72	289,43	0,1	39,8
217738E286E	97,49	291,18	97,59	291,08	0,1	0,1
217738E288E	256,3	310,9	241	309,87	15,3	1,03

Though these findings are encouraging, there is certainly room left for even more improvements. The collection of additional data from the real environment, testing of even more sophisticated algorithms, and incorporating new data sources can all contribute to increasing the accuracy of this model. This study serves as an example of how an RFID localization system based on machine learning can be created in the future.

5 Conclusion

Concluding, this paper stresses the significance of employing artificial intelligence algorithms, such as Support Vector Machines (SVM), in the improvement of the accuracy of indoor localization using the RFID technology. In spite of various challenges presented by the interference and complexities of environment, the application of machine learning techniques solves many drawbacks in traditional approaches. Experimental results demonstrate that an increased volume of data, even when generated artificially, can significantly reduce prediction errors. However, to make the system even more efficient, even stronger efforts need to be made for ac-quiring even larger real data, for finding even more complicated algorithms, and for using even newer data sources. This work thus promises even stronger and scalable RFID localization systems for various applications like logistics, medical, and security.

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