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Technische Universität Dresden

# On Deep Learning-based Techniques for Indoor Positioning Systems

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der Fakultät Elektrotechnik und Informationstechnik der Technischen Universität Dresden

zur Erlangung des akademischen Grades

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**Ivo Bizon Franco de Almeida**
*On Deep Learning-based Techniques for Indoor Positioning Systems*
Dissertation

**Vodafone Chair Mobile Communications Systems**
Institut für Nachrichtentechnik
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# Abstract

With the rising interest in integrating sensing functionalities into mobile wireless communication networks, and given the well-proven value of satellite-based positioning systems, this dissertation aims at exploring the potential of machine learning to contribute to the signal processing toolbox available to engineers for designing algorithms that enable precise and reliable positioning services indoors. The current techniques available for indoor positioning have come a long way, but an approach that is accurate to sub-meter levels in this case still remains elusive. The main reasons for this issue are: the hostile propagation characteristics of indoor environments, the difficulty in treating mathematical models that related the source position with the signal received at sensing units (SUs) and the mismatch of such models due to hardware impairments, the consequent computational complexity of proposed algorithms, and the absence of a straightforward parameter fusion mechanism.

To address these challenges, the work carried out in this dissertation proposes a neural network architecture that takes received signal strength (RSS) measurements from spatially distributed SUs as input and calculates the signal source coordinates in a supervised learning setting. RSS-based positioning is in focus due to its ability to deliver blind source localization, i.e., there is no positioning specific pilot signaling required, and the simple implementation complexity of the SUs needed to estimate the RSS.

The data-driven paradigm of machine learning employed is supervised learning, which turns the positioning algorithm also blind to propagation related variables, since these are embedded in the training data. Hence, within this dissertation, a positioning approach based on a fully connected deep neural network (DNN) is investigated and compared against classical model-based positioning algorithms both in numerical and experimental settings. The results suggest that the DNN scheme is able to provide source location estimates with

comparable performance to the maximum likelihood approach, while incurring significantly less online computational costs. Moreover, the ability of the DNN to scale and address the simultaneous multi transmitter positioning problem is also studied.

In an attempt to push the boundaries of positioning algorithms, the usage of a new source of location information – the position information correlation matrix (PICM) – is also proposed. This matrix is used as input to a convolutional neural network (CNN) that, in turn, outputs the source coordinates. This concept can be exploited in scenarios where a network of synchronized SUs is available. In contrast to the blind positioning possible through the pure RSS-DNN approach, the characteristics of the transmit signal can be optimized for enhancing the position representation ability of the PICM. Thus, guidelines for selecting the system parameters are examined.

The performance of the PICM-CNN technique is investigated employing a ray tracing simulation tool, which enables a fair comparison against other positioning approaches that rely on different sources of position information, such as time difference of arrival (TDoA) and RSS, within a common simulation framework. The outcomes of the numerical study demonstrate that the PICM-CNN approach can deliver an accurate indoor positioning service advancing the current state of art, showcasing its potential as a promising alternative for the future integration of wireless communication and sensing.

# Kurzfassung

Angesichts des steigenden Interesses an der Integration von Sensorfunktionen in mobile drahtlose Kommunikationsnetze und angesichts des bewährten Werts satellitengestützter Positionierungssysteme zielt diese Arbeit darauf ab, das Potenzial des maschinellen Lernens zu untersuchen, um einen Beitrag zum Signalverarbeitungs-Werkzeugkasten zu leisten, der Ingenieuren für die Konstruktion zur Verfügung steht Algorithmen, die präzise und zuverlässige Ortungsdienste im Innenbereich ermöglichen. Die derzeit verfügbaren Techniken zur Ortung in Innenräumen haben einen langen Weg zurückgelegt, aber ein Ansatz, der in diesem Fall auf den Submeterbereich genau ist, ist immer noch schwer zu finden. Die Hauptgründe für dieses Problem sind: die feindseligen Ausbreitungseigenschaften in Innenräumen, die Schwierigkeit, mathematische Modelle zu behandeln, die die Quellenposition mit dem an den *sensing units* (SUs) empfangenen Signal in Beziehung setzen, und die daraus resultierende Nichtübereinstimmung solcher Modelle aufgrund von Hardwarebeeinträchtigungen rechnerische Komplexität der vorgeschlagenen Algorithmen und das Fehlen eines einfachen Parameterfusionsmechanismus.

Um diese Herausforderungen anzugehen, skizziert die in dieser Arbeit durchgeführte Forschung zunächst eine neuronale Netzwerkarchitektur, die Messungen der *received signal strength* (RSS) von räumlich verteilten SUs als Eingabe verwendet und die Signalquellenkoordinaten in einer überwachten Lernumgebung berechnet. Die RSS-basierte Positionierung steht aufgrund der einfachen Implementierungskomplexität der SUs und ihrer Fähigkeit, eine blinde Quellenlokalisierung zu liefern, im Fokus, d. h. es ist keine positionierungsspezifische Pilotsignalisierung erforderlich.

Das verwendete datengesteuerte Paradigma des maschinellen Lernens ist überwachtes Lernen, das den Positionierungsalgorithmus auch für ausbreitungsbezogene Variablen blind macht, da diese in die Trainingsdaten eingebettet sind.

Daher wird im Rahmen dieser Arbeit ein Positionierungsansatz basierend auf einem vollständig verbundenen *deep neural network* (DNN) untersucht und mit klassischen modellbasierten Positionierungsalgorithmen sowohl in numerischen als auch experimentellen Umgebungen verglichen. Die Ergebnisse deuten darauf hin, dass das DNN-Schema in der Lage ist, Quellenstandortschätzungen mit vergleichbarer Leistung wie der Maximum-Likelihood-Schätzer zu liefern und dabei deutlich weniger Online-Rechenkosten verursacht. Darüber hinaus wird auch die Fähigkeit des DNN untersucht, das Problem der gleichzeitigen Positionierung mehrerer Sender zu skalieren und anzugehen.

Um die Grenzen der Positionierungsalgorithmen zu erweitern, wird auch die Nutzung einer neuen Quelle für Standortinformationen – der *position information correlation matrix* (PICM) – vorgeschlagen. Diese Matrix wird als Eingabe für ein *convolutional neural network* (CNN) verwendet, das wiederum die Quellkoordinaten ausgibt. Dieses Konzept kann von Anwendungen genutzt werden, bei denen ein Netzwerk synchronisierter SUs verfügbar ist. Im Gegensatz zur blinden Positionierung, die durch den reinen RSS-basierten DNN-Ansatz möglich ist, können die Eigenschaften des Sendesignals optimiert werden, um die Positionsdarstellungsfähigkeit des PICM zu verbessern. Dabei werden Richtlinien zur Auswahl der Systemparameter untersucht.

Die Leistung der PICM-CNN-Technik wird mithilfe eines Raytracing Simulationstool untersucht, das einen fairen Vergleich mit anderen Positionierungsansätzen ermöglicht, die auf unterschiedlichen Quellen von Positionsinformationen, wie z. B. *time difference of arrival* (TDoA) und RSS, innerhalb eines gemeinsamen Standorts basieren Simulationsrahmen. Die Ergebnisse der numerischen Studie zeigen, dass der PICM-CNN-Ansatz gegenüber dem Stand der Technik einen präzisen Indoor-Positionierungsdienst liefern kann, und zeigen sein Potenzial als vielversprechende Alternative für die zukünftige Integration von drahtloser Kommunikation und Sensorik.

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First and foremost, I would like to express my deepest gratitude to my supervisor, Professor Gerhard Fettweis, for his invaluable guidance, support, and patience throughout the course of this journey. His expertise and encouragement have been instrumental in shaping both the direction and the completion of this dissertation.

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# Contents


**1 Introduction** **1**

1.1 Motivation . . . 1

1.2 Structure & Contributions . . . 4

**2 Deep Learning Fundamentals** **7**

2.1 The Data Driven Paradigm: Task, Performance & Experience 9

2.2 Neural Network Architectures . . . 12

2.2.1 Fully Connected Neural Network . . . 13

2.2.2 Convolutional Neural Network . . . 15

2.3 Network Training . . . 18

2.4 Model Capacity, Underfitting, Overfitting, and Input Dimensionality . . . 22

2.5 Computational Complexity . . . 23

2.5.1 Training Complexity . . . 24

2.5.2 Inference Complexity . . . 24

2.6 Summary . . . 25

**3 Positioning Fundamentals** **27**

3.1 Measurement Models for Positioning Parameters . . . 27

3.1.1 Band-Limited Wireless Channel Model . . . 28

3.1.2 Received Signal Strength . . . 30

3.1.3 Time of Arrival & Time Difference of Arrival . . . 32

3.1.4 Angle of Arrival . . . 34

3.2 Classical Positioning Algorithms . . . 35

3.2.1 Time-based Methods . . . 37

3.2.2 Angle-based Methods . . . 39

3.2.3 RSS-based Methods . . . 41

3.3 Summary . . . 44

**4 Power-based Transmitter Positioning via Deep Neural Networks 47**
4.1 Proposed Neural Network Architecture . . . . . . . . . . . . . 49
4.2 Numerical Performance Evaluation . . . . . . . . . . . . . . . 53
4.2.1 Single Active Transmitter . . . . . . . . . . . . . . . . . 53
Considerations on Spatial Deployment of Sensing Units 54
Positioning Performance Analysis . . . . . . . . . . . . 56
Computational Complexity Analysis . . . . . . . . . . 59
4.2.2 Multiple Active Transmitters . . . . . . . . . . . . . . . 60
Positioning Performance Analysis . . . . . . . . . . . . 61
Classification Performance Analysis . . . . . . . . . . . 62
4.3 Experimental Performance Evaluation . . . . . . . . . . . . . 64
4.3.1 Measurement Setup . . . . . . . . . . . . . . . . . . . . 64
4.3.2 Estimation of Path Loss Model Parameters . . . . . . . 65
4.3.3 Positioning Performance Analysis . . . . . . . . . . . . 67
4.3.4 Notes on Model Lifetime . . . . . . . . . . . . . . . . . 70
4.4 Summary . . . . . . . . . . . . . . . . . . . . . . . . . . . . 70

**5 Correlation Matrix-based Transmitter Positioning via Convolutional Neural Networks 73**
5.1 Mathematical Definitions . . . . . . . . . . . . . . . . . . . . 74
5.2 Positioning Parameter Design . . . . . . . . . . . . . . . . . . 75
5.3 Proposed Neural Network Architecture . . . . . . . . . . . . . 78
5.4 Performance Evaluation . . . . . . . . . . . . . . . . . . . . . 79
5.4.1 Channel Model & Simulation Parameters . . . . . . . . 80
5.4.2 Static Simulation Environment . . . . . . . . . . . . . . 84
5.4.3 Dynamic Simulation Environment . . . . . . . . . . . . 86
5.5 Summary . . . . . . . . . . . . . . . . . . . . . . . . . . . . 88

**6 Conclusion & Outlook 89**
6.1 Conclusion . . . . . . . . . . . . . . . . . . . . . . . . . . . 89
6.2 Outlook . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 91

**A Appendix 93**
A.1 The Linear Chirp Signal . . . . . . . . . . . . . . . . . . . . 93
A.2 Classical Chirp Spread Spectrum . . . . . . . . . . . . . . . . 94
A.2.1 Long Range (LoRa) Physical Layer . . . . . . . . . . . 95
A.2.2 Chirp Spread Spectrum Maximum Likelihood Detection 96

Additive White Gaussian Noise Channel . . . . . . . . 97
Flat-fading Channel . . . . . . . . . . . . . . . . . . . . 98
Frequency-selective Channel . . . . . . . . . . . . . . . . 98
A.3 Enhanced Chirp Spread Spectrum Alternatives . . . . . . . . . 99
A.3.1 In-phase and Quadrature Chirp Spread Spectrum . . . 99
A.3.2 Discrete Chirp Rate Keying Chirp Spread Spectrum . . 102
A.4 Numerical Performance Simulation . . . . . . . . . . . . . . . . 105
A.4.1 Symbol and Bit Error Ratio Analysis . . . . . . . . . . 107
Additive White Gaussian Noise Channel . . . . . . . . 107
Time-variant Channel . . . . . . . . . . . . . . . . . . . 109
Time-variant Frequency-selective Channel . . . . . . . 111
A.5 Summary . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 113

**Bibliography** **115**

**Author Publications** **125**

# 1

# Introduction

## 1.1 Motivation

Satellite-based positioning[1] systems, named global navigation satellite systems (GNSSs) [ZKL19], received significant attention from the electrical engineering community over the past decades. GNSS has proven its value by its widespread adoption in either dedicated units, mobile phones and smartwatches, and an extensive number of location aware applications are used daily by these mobile devices. However, GNSS based positioning falls short in situations where clear line-of-sight (LoS) links between the mobile device and multiple satellites are not available. Such situations arise in dense urban environments and indoors. Furthermore, competing levels of availability and accuracy are hardly found in current commercial indoor-centric positioning systems, e.g., WiFi and Bluetooth Low Energy positioning systems. Hence, techniques that can help close this gap are certainly welcome in the development of future mobile communication networks.

Speculative perspectives on the sixth generation (6G) of mobile communications seem to agree on a strong interest on accurate indoor positioning techniques, since it has a central role in enabling the *connected intelligence* concept, where accuracy levels must be in the order of tens of centimeters [CBMD23]. This trend can be attributed to the increasing number of envisioned use cases in future wireless networks, where location information can be exploited for enhancing other services and the overall network performance [BYK+23]. Still within the foreseen technologies in 6G networks, integrated sensing and communications (ISAC) seeks to combine these two services by employing techniques which allow the shared usage of spectrum and hardware between

[1] The terms *location* and *position* are used interchangeably in this dissertation, and they refer to the Cartesian coordinates of one or more devices within an area of interest.

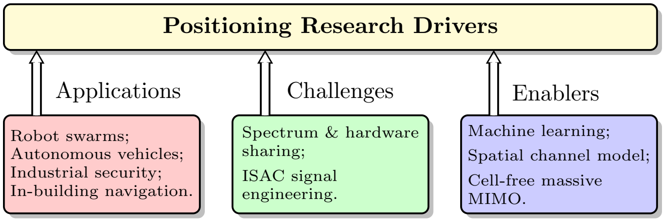


**Fig. 1.1.:** Main drivers of positioning research.

communications or sensing tasks [LCM+22]. Positioning is therefore a valuable feature of the sensing toolbox in the network, since location awareness can help to pave the way towards proactive flexible radio resource management by the network. Nevertheless, a set of challenges must be addressed to achieve the envisioned integration between the two services. Figure 1.1 highlights the main current drivers of positioning research, where the following challenges are identified: to develop a joint waveform design and signaling protocol that can tuned to achieve both sensing and communications performance requirements [WBV21; BC23]; to advance in the modeling of the wireless channel models that are not averaged over the spatial domain, i.e., geometric channel models; and to expand the use of nonlinear signal processing techniques. Despite the arguable future predictions about the usage of positioning services, established examples are enhanced emergency call systems. For example, E112 in Europe and E911 in the United States, have to provide positioning with 80% of the user equipments (UEs) at least 3 meters accuracy indoors for aiding rescue teams [Fed20].

The localization service under the assumption of an active signal source can be classified into two main categories: *self-positioning* and *remote-positioning*. The first corresponds to the case where a mobile device wants to know its position within a global, or local, coordinate system. Hence, the mobile user device processes the signals incoming from several anchor units with known locations for estimating its own position relative to the anchor points. In contrast, remote-positioning assumes what can be called a wireless sensor network (WSN), where multiple sensing units (SUs) are connected to a central unit (CU). The SUs collects incoming signals from the mobile device(s), and send them to the CU, where the source coordinates are estimated. In this dissertation, the focal point is remote-positioning. Nevertheless, the ideas presented here can be applied in self-positioning settings given that the mobile device has the required computing resources.

Positioning can be further classified as *cooperative* or *non-cooperative* whether the devices aid in their position estimation, e.g., by transmitting positioning specific signaling, or not. Non-cooperative remote-positioning is of particular interest in private wireless networks employed within factory plants, or large farming areas, since these are particularly threatened by accidental or intentional jamming transmissions. Arguably, security cameras can already address the problem of localizing non-authorized devices that can disturb the electromagnetic spectrum. However, a trained security crew must be always vigilant to spot violations and act within a fast time window. Moreover, privacy is always a concern against cameras, while radio sensing can be considered an alternative that is more suitable to preserve privacy, and is not constrained by walls as imaging systems are. To this end, the physical transmitter position is valuable information to detect and act against radio jamming from unauthorized transmitters [KFF19; ZGBG20]. In any case, proactive and privacy preserving localization of intentional or accidental interfering transmitters is a requirement for guaranteeing reliability and security in wireless networks [VM20]. On the other end, cooperative remote-positioning can be a key component in ISAC networks, since it can aid communications tasks, such as cell handover and beam selection, and thus allowing a more efficient distribution of resources among users [DBB+21]. By the same token, traditional mobile data communications can facilitate positioning by employing signalinaling waveforms with desirable properties.

The aforementioned scenarios require positioning services that are able to operate with accuracy in the order of 0.1 to 2 meters in harsh propagation conditions, and with minimal prior knowledge of the transmission protocol and propagation characteristics [BYK+23]. Thus, it seems certain to expected that accurate indoor positioning will play a key role in future wireless networks given the current trend in industry and research. Finally, artificial intelligence (AI) techniques are also envisioned as indispensable tools for achieving the required accuracy, precision, and real-time experience needed.

## 1.2 Structure & Contributions

The main contributions in this dissertation are structured as follows:

**Chapter 2** brings fundamental concepts in deep learning (DL) by presenting the basics of machine learning, where concepts such as model capacity, generalization, data dimensionality, network architectures, and network training are outlined. Moreover, motivations for the employment of data-driven algorithms in the context of positioning are introduced.

**Chapter 3** presents an overview of fundamental concepts employed for device positioning. Its first subsection contains a description of the general band limited multipath wireless channel model followed by the measurement models of time of arrival (ToA), time difference of arrival (TDoA), angle of arrival (AoA), and received signal strength (RSS). The second subsection shows a selection of position estimation algorithms together with the theoretical limits of RSS-based positioning under spatially correlated log-normal shadowing noise.

**Chapter 4** contains the detailed description of a power-based blind transmitter positioning scheme employing DL. In this chapter, the performance of this approach is investigated under simulated and experimental scenarios, and compared against classical and as well as recently proposed positioning techniques. It is observed that through real-world measurements the proposed DL localization framework is able to exploit propagation and hardware signatures, that are not captured by classical model driven positioning techniques, to deliver more accurate location estimates while presenting lower online computational complexity. Furthermore, the performance of our DL localization scheme when the training data are synthetically generated with a path loss model (PLM) is analyzed. This provides insights into the localization performance that can be achieved when no measured data are available, and only theoretical knowledge on propagation is used. Furthermore, an extension of the proposed scheme to multiple sources is investigated. The contributions of this chapter have been reported in the following publications:

- **I. B. F. de Almeida**, M. Chafii, A. Nimr and G. Fettweis, "Blind Transmitter Localization in Wireless Sensor Networks: A Deep Learning Approach," *2021 IEEE 32$^{nd}$ Annual International Symposium on Personal, Indoor and Mobile Radio Communications PIMRC*, Helsinki, Finland, 2021 [dACNF21].

- **I. Bizon**, Z. Li, F. Burmeister and G. Fettweis, "Indoor Received Power Measurements Associated with Reference Transmitter Location using Wireless Sensor Network", *IEEE Dataport*, Aug. 2022 [BLBF22].

- **I. Bizon**, Z. Li, A. Nimr, M. Chafii and G. P. Fettweis, "Experimental Performance of Blind Position Estimation Using Deep Learning," *2022 IEEE Global Communications Conference GLOBECOM*, Rio de Janeiro, Brazil, 2022 [BLN+22].

- **I. Bizon**, A. Nimr, P. Schulz, M. Chafii and G. P. Fettweis, "Blind Transmitter Localization Using Deep Learning: A Scalability Study," *2023 IEEE Wireless Communications and Networking Conference WCNC*, Glasgow, United Kingdom, 2023 [BNS+23].

**Chapter 5** presents the investigation of an alternative positioning technique which relies on synchronization among SUs for defining an information parameter named position information correlation matrix (PICM). This feature is then employed in a coherent DL-based localization approach which is able to outperform classical positioning techniques that rely solely on RSS or TDoA for source coordinate estimation. The definition of the PICM, and how the system sampling frequency and transmit signal auto-correlation properties affect the positioning performance are explored. Recommendations for obtaining the ideal parameters are also devised. The positioning performance is investigated under a scenario whose propagation effects are based on a ray tracing simulator, which provides accurate spatial information for supporting the obtained results and comparison with classical positioning parameters. The contributions of this chapter have been reported in the following publications:

- **I. Bizon**, A. Nimr, G. Fettweis , and M. Chafii, "Indoor Positioning Using Correlation Based Signal Analysis and Convolutional Neural Networks," *$19^{th}$ International Symposium on Wireless Communication Systems ISWCS*, Rio de Janeiro, Brazil, 2024 [BNFC24].

**Chapter 6** concludes the dissertation with closing remarks and points out directions for future research on source positioning systems.

**Appendix A** presents an investigation on data transmission employing spread spectrum techniques that are based on the chirp waveform. The contributions of this chapter have been reported in the following publications:

- **I. B. F. de Almeida**, M. Chafii, A. Nimr and G. Fettweis, "In-phase and Quadrature Chirp Spread Spectrum for IoT Communications," *GLOBECOM 2020 - 2020 IEEE Global Communications Conference*, Taipei, Taiwan, 2020 [dACNF20].