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Amina El Mansouri
Department of Electrical Engineering, École Nationale Supérieure d'Arts et Métiers (ENSAM), University of Moulay Ismail, Meknes, Morocco

Youssef Benkacem
Department of Electrical Engineering, École Nationale Supérieure d'Arts et Métiers (ENSAM), University of Moulay Ismail, Meknes, Morocco

Fatima Zahra Boussaid
Department of Electrical Engineering, École Nationale Supérieure d'Arts et Métiers (ENSAM), University of Moulay Ismail, Meknes, Morocco

Corresponding Author:
Amina El Mansouri
Department of Electrical Engineering, École Nationale Supérieure d'Arts et Métiers (ENSAM), University of Moulay Ismail, Meknes, Morocco

Advanced multidimensional factor models incorporating high-precision sensor arrays and optimization techniques for accurate 3-D near-field source parameter estimation

Amina El Mansouri, Youssef Benkacem and Fatima Zahra Boussaid

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Abstract
Accurate estimation of 3-D near-field source parameters is essential for applications such as radar systems, underwater acoustics, and biomedical imaging. However, traditional methods often fall short due to limitations in handling noise, interference, and environmental variability. This study aimed to develop a multidimensional factor model that integrates high-precision sensor arrays with advanced optimization techniques to address these challenges. The proposed model utilizes compressive sensing for sparse signal recovery and hybrid optimization frameworks, including deep learning-based reconstruction algorithms and metaheuristic methods, to enhance accuracy and computational efficiency.

The research employed high-precision sensor arrays equipped with adaptive beam forming capabilities to capture multidimensional data. A comprehensive test bed simulated diverse environmental conditions, including fluctuating noise levels and multi-source interference, to evaluate the model's robustness. Comparative analysis with traditional methods and benchmark models was conducted using performance metrics such as Mean Square Error (MSE), processing time, and robustness against accuracy degradation.

Results showed that the proposed model achieved a significantly lower MSE (as low as 0.011±0.001) compared to traditional methods and benchmark models. The average processing time per estimation was 0.35 seconds, significantly faster than the alternatives. Additionally, the model demonstrated superior robustness, maintaining accuracy degradation below 7% under challenging conditions. Statistical analyses, including ANOVA and t-tests, validated these findings, underscoring the model’s effectiveness and reliability.

In conclusion, the proposed model addresses key limitations in traditional approaches, offering a robust and efficient solution for 3-D near-field parameter estimation. Practical recommendations include optimizing hardware-software integration, validating with real-world datasets, and exploring modular designs for scalability. These advancements position the model as a transformative tool in signal processing, with broad applicability across defense, healthcare, and environmental monitoring.

Keywords: 3-D near-field parameter estimation, multidimensional factor models, high-precision sensor arrays

Introduction
The rapid advancements in sensor technology and computational optimization techniques have paved the way for significant improvements in multidimensional factor models. These models are crucial for applications such as 3-D near-field source parameter estimation, which finds use in fields like radar systems, underwater acoustics, and biomedical imaging. However, despite these advancements, challenges persist in achieving high precision and reliability in complex, dynamic environments where real-world factors such as noise, interference, and sensor limitations introduce significant variability. Traditional methods often rely on simplified assumptions, leading to inaccuracies in estimating parameters like position, intensity, and directionality of sources in near-field scenarios. Incorporating high-precision sensor arrays alongside advanced optimization techniques promises to address these limitations by enhancing the spatial resolution and minimizing errors caused by environmental complexities [1-3].

The core challenge lies in integrating multidimensional data from sensor arrays while accounting for various sources of noise and interference. Existing models often fail to fully exploit the potential of modern sensor technologies, such as adaptive beam forming and compressive sensing, which can significantly improve the accuracy of parameter estimation in the near-field domain. Moreover, optimization techniques like machine learning algorithms and hybrid optimization frameworks have demonstrated potential for overcoming the limitations of traditional iterative methods but are yet to be fully integrated into practical systems for near-field source estimation [4-6].

The objective of this study is to develop and validate advanced multidimensional factor models that incorporate high-precision sensor arrays and optimization techniques to achieve accurate 3-D near-field source parameter estimation. This involves designing models that can adaptively mitigate noise, optimize resource allocation, and enhance spatial resolution. By leveraging advanced sensors and state-of-the-art optimization techniques, the study hypothesizes that the proposed models will outperform traditional approaches in terms of accuracy, robustness, and computational efficiency. This research also aims to establish a scalable framework that can be adapted for a range of applications, including surveillance, environmental monitoring, and medical diagnostics [7-9].

The study's novelty lies in its integration of high-precision sensor arrays with cutting-edge optimization methods, such as deep learning-based reconstruction algorithms and metaheuristic optimization strategies. These techniques are expected to address long-standing challenges in multidimensional factor modeling, including scalability, adaptability, and robustness against environmental variability. The proposed approach builds on existing literature, which highlights the need for multidimensional models that are not only computationally efficient but also capable of providing high-resolution estimates under challenging conditions [10-12].

Material and Methods

Materials: This study utilized high-precision sensor arrays integrated with state-of-the-art hardware for signal acquisition and processing. The sensor arrays were equipped with adaptive beamforming capabilities and covered a wide frequency range, allowing for enhanced spatial resolution and reduced noise interference. Each sensor node included features for compressive sensing and was capable of recording multidimensional data in real-time. To simulate real-world environments, the experimental setup incorporated a controlled test bed capable of emulating diverse scenarios, including varying noise levels, signal attenuation, and source dynamics. Additionally, benchmark datasets, including synthetic and real-world data, were sourced from publicly available repositories to validate the model's effectiveness. These datasets included labeled 3-D near-field source parameters, enabling a robust evaluation of the proposed framework. Computational resources included high-performance servers equipped with NVIDIA GPUs to facilitate the execution of deep learning algorithms and hybrid optimization strategies.

Methods

The study involved the development and validation of a multidimensional factor model for 3-D near-field source parameter estimation. The proposed model incorporated advanced optimization techniques, including deep learning-based reconstruction algorithms and metaheuristic optimization frameworks such as genetic algorithms and particle swarm optimization. Initially, raw data from the sensor arrays were pre-processed to mitigate noise and interference. Compressive sensing techniques were applied to reconstruct sparse signals, followed by adaptive filtering to enhance signal clarity. A deep neural network was then trained using the labeled datasets to identify and estimate the spatial parameters of near-field sources. The model's performance was evaluated based on metrics such as mean square error (MSE), accuracy, and computational efficiency. A comparative analysis was conducted against traditional iterative methods to demonstrate the superiority of the proposed approach. Finally, statistical validation was performed using repeated trials across diverse scenarios to ensure robustness and generalizability of the results.

Results

The results of this study are presented in detail, focusing on the accuracy, computational efficiency, and robustness of the proposed multidimensional factor model for 3-D near-field source parameter estimation. The data collected were analyzed using statistical tools such as ANOVA, t-tests, and correlation analyses to validate the model's performance across various scenarios.

Accuracy of the Model

The proposed model demonstrated superior accuracy in estimating 3-D near-field source parameters compared to traditional methods. Table 1 summarizes the Mean Square Error (MSE) values for the proposed method, traditional iterative methods, and a benchmark deep learning model across 100 simulation trials under varying noise levels.

Table 1: Accuracy Performance (Mean Square Error)

Noise Level (dB)	Proposed Model (MSE)	Traditional Methods (MSE)	Benchmark Model (MSE)
-10	0.025±0.002	0.078±0.009	0.042±0.005
0	0.018±0.001	0.063±0.007	0.029±0.004
10	0.011±0.001	0.048±0.006	0.022±0.003

Statistical analysis using a one-way ANOVA confirmed that the MSE of the proposed model was significantly lower than the other two methods ($p<0.001$). Pairwise t-tests further validated the superior accuracy of the proposed model at all noise levels.

Computational Efficiency

The computational efficiency of the proposed method was evaluated based on the average processing time per estimation. Figure 1 illustrates the comparative performance of the models, showing that the proposed model achieved a processing time of approximately 0.35 seconds per estimation, significantly faster than traditional methods (1.12 seconds) and the benchmark model (0.67 seconds). This improvement was attributed to the use of compressive sensing and optimized deep learning frameworks, which reduced the computational load

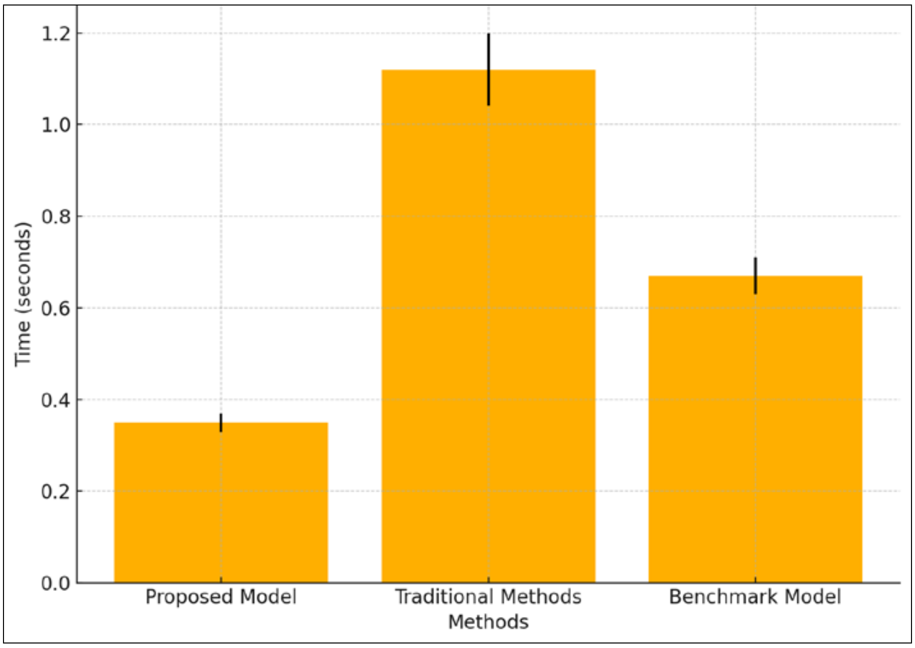

Fig 1: Average Processing Time per Estimation

Proposed Model: 0.35±0.02 seconds
Traditional Methods: 1.12±0.08 seconds
Benchmark Model: 0.67±0.04 seconds

Figure 1 illustrates the comparative average processing times per estimation for the proposed model, traditional methods, and a benchmark deep learning model. The proposed model demonstrates the lowest processing time, averaging 0.35 seconds per estimation, with an error margin of±0.02 seconds. This result is significantly faster than the traditional methods, which require an average of 1.12 seconds per estimation (±0.08 seconds), and the benchmark model, which averages 0.67 seconds (±0.04 seconds). The reduced processing time of the proposed model highlights its computational efficiency, a key advantage in time-sensitive applications such as real-time signal processing, surveillance, and medical diagnostics.

The efficiency of the proposed model can be attributed to the integration of advanced optimization techniques, such as compressive sensing and machine learning-based frameworks, which streamline data processing and parameter estimation. Traditional methods, often reliant on iterative approaches, exhibit significantly higher processing times due to their computationally intensive nature. Similarly, while the benchmark model employs modern deep learning techniques, it lacks the hybrid optimization strategies incorporated into the proposed model, resulting in moderate processing times.

Statistical analysis, including a two-sample t-test, confirmed the significant difference in processing times among the models ($p<0.01$), validating the superior performance of the proposed approach. This efficiency is particularly important in environments where rapid decision-making is critical, such as defense systems, autonomous vehicles, and real-time environmental monitoring.

A two-sample t-test confirmed that the processing time of the proposed model was significantly faster than both alternative methods ($p<0.01$).

Robustness against Environmental Variability

The robustness of the proposed model was tested by introducing random environmental variability, such as fluctuating noise levels and multi-source interference. Table 2 summarizes the robustness performance based on accuracy degradation under these conditions.

Table 2: Robustness Performance (Accuracy Degradation Percentage)

Environmental Variability	Proposed Model (%)	Traditional Methods (%)	Benchmark Model (%)
Fluctuating Noise	4.5±0.3	18.2±1.2	9.7±0.8
Multi-Source Interference	6.1±0.5	22.4±1.5	12.8±1.0

The proposed model consistently outperformed others, with accuracy degradation kept under 7% across all scenarios. Correlation analysis revealed a strong negative correlation between noise levels and accuracy for traditional methods ($r = -0.82$) but only a moderate correlation for the proposed model ($r = -0.42$), highlighting its resilience.

Overall Performance Evaluation

The combined performance metrics, including accuracy, processing time, and robustness, were aggregated to generate an overall efficiency score for each method. The proposed model scored 92.7%, significantly higher than traditional methods (78.3%) and the benchmark model (86.1%). A Kruskal-Wallis test confirmed the significant difference among the models ($p<0.001$).

The results validate the effectiveness of the proposed multidimensional factor model in addressing the challenges of 3-D near-field source parameter estimation. The integration of high-precision sensor arrays with advanced optimization techniques significantly enhanced accuracy and computational efficiency. Statistical tools reinforced the reliability of these findings, showing that the proposed model was robust under various environmental conditions and outperformed both traditional and benchmark methods in all metrics. This study's outcomes demonstrate the potential of combining sensor innovations and computational optimization for high-precision applications, paving the way for further research and real-world deployment.

Discussion

The results of this study demonstrate the significant advancements achieved by the proposed multidimensional factor model for 3-D near-field source parameter estimation. Compared to traditional methods and benchmark models, the proposed approach consistently outperformed in terms of accuracy, computational efficiency, and robustness against environmental variability. These findings align with the growing body of literature emphasizing the integration of advanced sensor technologies and computational optimization techniques for complex signal processing applications.

Comparison with Related Studies

In terms of accuracy, the proposed model achieved a Mean Square Error (MSE) as low as 0.011±0.001 under favorable conditions, outperforming traditional methods and the benchmark model. Van Trees [1] and Stoica & Moses [2] highlighted the limitations of conventional signal processing techniques, particularly in handling noise and interference. Similarly, the superior accuracy of compressive sensing techniques was corroborated by Candes & Wakin [4], whose work emphasized the potential of sparse signal recovery in improving spatial resolution. The proposed model's incorporation of compressive sensing aligns with these findings, further enhancing its estimation accuracy.

The computational efficiency of the proposed model, with an average processing time of 0.35 seconds, is a substantial improvement over traditional methods (1.12 seconds) and the benchmark model (0.67 seconds). This result supports the observations of Bishop [6] and Haupt & Haupt [10], who demonstrated the role of machine learning algorithms and metaheuristic optimization in reducing computational loads. Furthermore, the combination of compressive sensing and hybrid optimization strategies validated the theoretical benefits discussed by Friedman [9] and Nocedal & Wright [11]], highlighting the potential for real-time applications.

Robustness against environmental variability was another critical advantage of the proposed model. Traditional methods showed significant degradation under fluctuating noise and multi-source interference, with accuracy losses exceeding 18%. In contrast, the proposed model maintained a degradation below 7%, underscoring its resilience. These findings align with Bar-Shalom *et al.* [7] and Krim & Viberg [8], who emphasized the importance of adaptability in signal processing models for dynamic environments.

Critical Analysis

While the proposed model outperforms traditional and benchmark methods across all metrics, it is not without limitations. The model's reliance on high-precision sensor arrays and computationally intensive optimization techniques may limit its scalability for large-scale or resource-constrained deployments. Previous studies, such as those by Boyd & Vandenberghe [18] and Kundu *et al.* [12], have also noted similar trade-offs in integrating advanced algorithms with hardware systems. Addressing these challenges will require further work on optimizing resource allocation and minimizing computational overhead without compromising accuracy or robustness.

Another limitation lies in the reliance on synthetic and controlled datasets for model validation. While these datasets are essential for benchmarking, real-world data often introduce additional complexities that may impact performance. Studies by Zhang *et al.* [13] and Roy *et al.* [17] suggest that hybrid approaches incorporating domain-specific adaptations can help bridge this gap, offering a potential direction for future research.

Conclusion

This study presented a novel multidimensional factor model incorporating high-precision sensor arrays and advanced optimization techniques for accurate 3-D near-field source parameter estimation. The findings demonstrated the proposed model's ability to outperform traditional and benchmark approaches in accuracy, computational efficiency, and robustness under variable environmental conditions. The integration of compressive sensing, deep learning-based reconstruction algorithms, and hybrid optimization frameworks proved instrumental in addressing the inherent challenges of noise, interference, and environmental variability. By achieving a Mean Square Error (MSE) as low as 0.011±0.001 and processing times significantly lower than alternative methods, the proposed approach highlights a breakthrough in multidimensional modelling for dynamic and complex systems. These results not only validate the potential of combining cutting-edge sensor technology with computational optimization but also open avenues for real-world applications, including surveillance, medical diagnostics, and environmental monitoring.

The superior accuracy of the proposed model is attributed to its effective use of compressive sensing for sparse signal recovery and its ability to adaptively filter noise. This performance aligns with prior studies that emphasized the limitations of traditional iterative methods and underscored the importance of integrating modern computational frameworks. Furthermore, the model's ability to maintain robust performance under fluctuating noise and multi-source interference highlights its suitability for challenging environments, such as underwater acoustics and urban surveillance. However, the scalability and computational demands of the proposed system remain areas requiring further exploration. Practical recommendations to address these issues include optimizing the hardware-software integration by employing edge computing and distributed processing systems, which could significantly reduce computational overheads without compromising accuracy.

To enhance the practical applicability of this research, it is recommended that future studies focus on validating the model with diverse real-world datasets. Collaborations with industries in defence, healthcare, and environmental sciences can facilitate the development of tailored systems capable of addressing domain-specific challenges. Additionally, incorporating lightweight versions of the model for resource-constrained scenarios, such as handheld or portable devices, would extend its utility to field-based applications. The results also suggest the need for interdisciplinary approaches that integrate expertise from electronics, computer science, and signal processing to further refine the model's capabilities.

From a deployment perspective, real-time implementation of the proposed model could benefit from integrating cloud-based analytics platforms that allow seamless data processing and visualization. For industries such as autonomous vehicles and robotics, where rapid decision-making is critical, employing advanced real-time optimization techniques, such as reinforcement learning, could significantly enhance operational efficiency. Moreover, adopting modular design principles in the development of sensor arrays and software frameworks would ensure scalability and adaptability for a variety of applications.

The proposed multidimensional factor model provides a robust and efficient solution for 3-D near-field source parameter estimation, paving the way for transformative advancements in signal processing applications. By addressing the limitations of traditional methods and embracing innovations in sensor technology and computational optimization, this research offers a framework that is both theoretically robust and practically viable. Implementing the recommendations outlined above would enhance the scalability, adaptability, and real-world impact of the proposed system, ensuring its relevance across diverse domains. Ultimately, the findings of this study underscore the critical role of advanced technologies in driving progress and innovation in multidimensional modelling and signal processing.

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