Review Article

Modern Deep Learning Accelerometer Denoising Methods For Mobile Robot Dead-Reckoning: A Review

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ABSTRACT

This paper reviews recent deep learning methods aimed at reducing random errors in low-cost microelectromechanical systems (MEMS) inertial sensors for mobile robot dead reckoning. Accurate localization remains a critical challenge in GPS-denied environments, particularly for platforms that rely solely on accelerometer data. Four representative studies were selected based on architectural novelty and relevance to inertial-only dead reckoning. The review analyzes their denoising strategies, including Generative Adversarial Networks (GANs), Physics-informed Neural Nets, Wave-U-Nets, k Nearest Neighbors (kNN), as well as their performance across evaluation metrics such as Absolute Trajectory Error (ATE), Relative Trajectory Error(RTE), and Relative Rotation Error (RRE). Hardware platforms and tasks are also compared to assess generalizability. Findings indicate that research in range extension remains limited but suggest that generative architectures are promising for improving accelerometer signal reconstruction. Further, the lack of unified experimental datasets highlights an opportunity for standardization in future work. Overall, this review emphasizes that unified metrics and methods are key to advancing practical inertial-based dead reckoning in low-cost mobile robots.

Keywords: Accelerometer; denoising; deep-learning; mobile-robot; dead-reckoning

INTRODUCTION

Mobile Robots play an increasingly critical role in multiple industries, such as manufacturing, exploration, and the military. Given that mobile robots often perform tasks autonomously, accurate positioning is crucial for faster and more precise procedures. Localization is a process where the robot's position is estimated based on sensor data. A subset of localization is dead-reckoning, where position and orientation are calculated using previous measurements of acceleration and angular velocity (1).

In most localization algorithms for mobile robots, a variety of sensors are used together to create a more accurate estimate of the position (1). A commonly used sensor is the Inertial Measurement Unit (IMU). For positioning and orientation information, angular velocity is integrated once to find orientation, while acceleration is integrated twice to find position (1). IMUs made with low-cost microelectromechanical systems (MEMS) often suffer from low sensitivity, high random walk noise, and temperature drift, making them hard to use directly for position estimates (2). Instead, an alternative system used for robot localization is a combination of a Global Navigation Satellite System (GNSS) with an IMU. The sensors complement each

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other with the GNSS providing stable position data, while the accelerometer provides acceleration and orientation data with a higher output rate (3).

Further, a common problem arises when mobile robots are used in indoor applications. This is because GNSS is much less reliable indoors for positioning. Instead, engineers have resorted to fusing vision or distance sensor data with accelerometer data (1). Some common algorithms used for such applications include Kalman and particle filters. At the same time, sensors such as vision and distance still suffer from similar disadvantages as GNSS (1). There are often obstacles that can interfere with sensor readings, reducing range and accuracy. Specifically for wheeled mobile robots, wheel odometer data could also be used. However, due to bumps and wheel slippage, odometer data also has inaccuracies in different environments. Therefore, improving IMU data quality is key to enhancing sensor fusion and stand-alone dead-reckoning performance. Filtering methods such as Kalman filtering, wavelet transforms, and Empirical Mode Decomposition have been proposed to denoise accelerometer signals and reduce drift. Kalman filters rely on models of process and measurement noise, as well as system linearity, to deliver optimal mean-square error estimates; mismatches in Q, R, or model structure can degrade accuracy. Wavelet-based techniques, particularly discrete wavelet transforms, can be computationally efficient but depend on careful choice of wavelet basis, scales, and thresholds, especially in noisy, complex, or nonstationary signals (4).

Initially, researchers attempted to use 1-layer artificial neural networks to learn the measurement errors of gyroscopes and approximate gyro drifts (2). In recent years, deep learning methods have been designed to filter accelerometer data with more accuracy than traditional data-based methods. Currently, researchers have used multiple approaches that use deep learning to denoise accelerometer data. In this article, algorithms will be categorized by the aspect of low-cost IMU signals that they enhance and the type of training data they require.

A key limitation of deep learning algorithms for inertial data processing is their dependence on labeled datasets tailored to specific tasks, sensors, or environments (6). Models trained in one scenario, such as indoor pedestrian tracking, often fail to generalize well to other contexts, like vehicle motion or aerial navigation (2). Additionally, the field lacks standardized datasets, benchmarks, and evaluation protocols, making it difficult to compare model performance across studies. Neural networks used in this domain typically function as black boxes, with architectures and loss functions custom-tuned to individual applications (2). This leads to significant variability in evaluation methods and metrics. In contrast, many studies on inertial positioning adopt common performance indicators such as Absolute Trajectory Error (ATE) and Relative Trajectory or Rotation Errors (RTE/RRE), which are typically calculated as Root Mean Square Error (RMSE) over trajectory segments or relative poses (2).

In addition to attempts made for accelerometer denoising in general, some algorithms were devised for inertial-based dead-reckoning of wheeled mobile robots. Due to the complex nature of MEMS accelerometer noise, multiple approaches exist for denoising accelerometer data, from improving calibration, reducing random error, increasing range, and fusing with different sensors. At an application level, there is less focus on inertial-only dead-reckoning for wheeled mobile robots due to the prevalence of other cheap sensors relied on for localization. This review focuses on deep learning (DL) methods for accelerometer denoising in inertial-only dead reckoning algorithms. Key research gaps identified include the limited real-time implementation of DL techniques, the absence of unified evaluation metrics, and insufficient investigation into over-range signal reconstruction.

DEEP LEARNING APPROACHES FOR ACCELEROMETER DENOISING

HEROS-GAN: Generative Models for Range Extension

Honed-Energy Regularized and Optimal Supervised Generative Adversarial Network (HEROS-GAN) is a novel deep learning framework developed by Yifeng Wang and Yi Zhao at the Harbin Institute of Technology (6). HEROS-GAN enhances the performance of low-cost accelerometers by transforming their signals into high-quality equivalents. The model addresses the problem of range extension for accelerometer denoising by using a Generative deep learning approach. Optimal Transport Supervision (OTS) and Modulated Laplace Energy (MLE) enable the model to function in the absence of frame-wise paired data, which generative models typically require (6). By analyzing feature similarities, the model aligns signals from inexpensive sensors with those from higher-quality sensors.

In addition, MLE introduces a modulated Laplace energy regularization that encourages the generator to preserve local high-frequency features, thereby improving resolution and recovering signal dynamics otherwise lost in low-cost sensor data. The researchers' ablation study utilizes CycleGAN as the base model and describes how OTS and MLE enable the model to perform better in dynamic conditions, with the greatest reduction in Clipped Signal Reconstruction Error (CSRE) due to MLE and the greatest reduction in Zero Velocity Residual Error (ZVRE) due to OTS (6).

To support this architecture, the authors introduced the Low-Cost Accelerometer Signal Enhancement Dataset (LASED), the first known large-scale dataset for unpaired enhancement of accelerometer signals. LASED contains hundreds of unpaired high- and low-quality accelerometer samples, including signals across different motion types and devices (6). A notable concern may arise from the impact of data augmentation on physical plausibility and generalization, particularly in erratic movements that may remain outside the sensor range for extended time periods.

PILOT: Physics-Informed Denoising Framework

Zhang *et al*. propose PILOT (Physics-Informed Learning for denoising Technology), a real-time sensor denoising framework that incorporates known physical relationships directly into the learning objective. Unlike conventional approaches that rely on clean or paired ground truth data, PILOT applies a physics-based loss function as a soft constraint, enabling the model to reconstruct physically plausible signals using only noisy sensor inputs (7). The training is divided into two phases: a supervised pretraining stage using synthetically corrupted data, followed by physics-guided fine-tuning on real-world measurements. This two-stage process improves convergence by preventing the model from emphasizing the physics loss over reconstruction accuracy. PILOT has been validated across diverse sensing domains, including inertial navigation, CO_2 concentration monitoring, and HVAC control with state-of-the-art results. Notably, it demonstrates the highest physics alignment of all evaluated models in (7), with an acceleration Mean Square Error (MSE) of 1.8695, significantly less than the next-best model (MSE = 118.7). It processes one second of sensor data in approximately 4 ms, making it suitable for real-time applications on edge devices. The only constraint is the requirement of a definable physical relationship between sensor signals (7).

To further support the physical plausibility of their model, the researchers included evaluations on the downstream performance of PILOT compared to other models in inertial navigation settings. The data provided demonstrates that PILOT outperforms all other evaluated models in (7) in ATE and RTE. Overall, it is stated that well-defined physics models and faster sampling rates lead to larger performance improvements, making PILOT particularly promising for IMU denoising (7).

ADNet: Attention-Enhanced Wave-U-Net Architecture

Zheng *et al*. present ADNet, a neural network model designed to denoise accelerometer signals under real-world noise conditions and reduce the signal distortion often introduced by traditional filtering methods. The architecture is based on a 1D U-Net structure with four encoder and four decoder layers and enhanced by attention mechanisms for improved feature extraction. Specifically, ADNet incorporates Channel Attention (CA) modules in skip connections and applies Multi-Head Self-Attention (MHSA) between the encoder and decoder to better capture temporal dependencies. The decoder is further modified with 1D convolutional layers to improve signal reconstruction. Experimental results on the Walking Speed and Field Experiment datasets show that ADNet significantly outperforms both traditional denoising filters (e.g., moving average, Savitzky-Golay) and deep learning baselines (e.g., CNN, LSTM, TCN), achieving more than an order of magnitude improvement in MSE, Mean Absolute Error (MAE), and RMSE. Unlike its base model, Wave-U-Net, whose outputs tend to introduce distortion, ADNet better preserves the underlying signal structure by focusing on key feature information (8). However, the model requires paired noisy-clean data for training, which can limit its applicability in scenarios where reference signals are difficult to obtain.

kNN: Non-Parametric Memory-Based Denoising

In the study by Engelsman and Klein (2022) from the University of Haifa, the motivation for using k-Nearest Neighbors (kNN) stemmed from the limitations of traditional filters and deep learning methods in processing stationary accelerometer signals during coarse alignment phases in navigation systems. Traditional models often fail to generalize well under low-dynamic conditions, and deep learning approaches require substantial motion data and long training periods. The kNN algorithm was employed as a non-parametric, memory-based denoising technique. For each accelerometer reading, the algorithm searched a large temporal window to identify k past signal segments with similar patterns, then averaged them to reconstruct a cleaner signal. This approach utilizes the self-similarity of stationary data, effectively reducing noise without requiring a training phase or labeled data. kNN has the least acceleration RMSE, and MAE compared to other methods in (9), representing how it outperforms both traditional filters (e.g., Kalman) and deep learning models (e.g., Gated Recurrent Unit (GRU), Long Short-Term Memory (LSTM)) in denoising accuracy. It performed particularly well on the experimental data set for acceleration RMSE, with an order of magnitude improvement over the raw signal. However, a potential drawback of using a kNN-based method is its poor ability to scale to larger datasets because it has the highest Big O time complexity compared to the methods covered in (9). Additionally, the memory required increases with dataset size, potentially demonstrating a use case for short stationary signals. Although not a deep learning model, kNN was included in this study due to its rarity in literature and use in static conditions.

In the past, numerous models and groups of models have been created and surveyed for accelerometer denoising. Previous surveys, such as (4), classify and discuss algorithms including Kalman, Wavelet, EMD, sensor fusion, and some deep learning algorithms such as LSTM and GRU. Building on previous studies, this study focuses on a few key areas of IMU filtering, including range extension and noise reduction. At the same time, limitations such as real-time usage and the ability to use unpaired data is discussed (Table 2).

Table 1. Summary of deep learning and non-deep learning denoising algorithms for MEMS accelerometers. The table compares error types addressed, real-time capability, dataset type (simulated vs. experimental), paired data requirements, and hardware platforms used in validation

Algorithm	Task Analysis	Online/Offline (real time or not)	Simulated or Real Data	Environment	Training Data type (paired/unpaired)
HEROS-GAN (6)	Noise reduction Range extension	Offline	Experimental (created their own data set LASED)	NVIDIA RTX 4090 GPU	unpaired
PILOT (7)	Drift reduction noise reduction increased physical consistency	Offline	Experimental and simulated	NVIDIA RTX A6000 (with 48GB memory), AMD EPYC 7452 32-Core Processor, and Ubuntu 18.04.5 LTS.	unpaired
ADNet (8)	Noise reduction Reduce signal distortion	Offline	Simulated and experimental	Implemented on PyTorch and trained on a single NVIDIA 3080TiGPU	paired
kNN (9)	Noise Reduction in stationary signals	Offline	Experimental	(Intel i5-9600K CPU @3.70 GHz and NVIDIA GTX2080 GPU	NA (kNN non-parametric)

Table 1 above summarizes which type of error the algorithm handles, whether it is real time or not, and which type of dataset it was tested on. In this review, simulated datasets refer to artificially generated IMU data, typically derived by statistically perturbing clean signals rather than collecting them via physical experiments. It also provides whether the algorithm requires paired data as well as the platform it was tested on. There was not much description on what specific type of noise was handled in the text. However, this information was deduced from a combination of both words from the discussion section of the papers, as well as the data they provided.

Table 2. Structural overview, strengths, and limitations of representative accelerometer denoising methods. Each model's architecture is briefly described, along with key advantages and shortcomings, to highlight relative performance trade-offs.

Algorithm	Architecture	Strengths	Weaknesses	Relative Comparison
HEROS-GAN (6)	CycleGAN as a baseline, while using OTS and MLE loss functions	Works on unpaired low-cost IMU trainingdata Increases the range and decreases noise for IMUs. Performs better than previous models on larger clipped sections in CSRE	Requires a complex GAN architecture, has potential instability when using unrestricted laplace rmancedepends on feature alignment and modulation parameters	Does not require additional information to handle unpaired data, but uses customized loss functions, and may have physical plausibility 13sues compared to other methods such as PILOT
PILOT(7)	Has two loss functions, reconstruction loss and physics loss. Is trained using a Convolutional Neural Network Uses two-stage training, first without physics loss, then with physics loss	Excels in inertial Navigation Greater performance gains from fast sampling systems such as IMU Denoises without ground truth Real time capability on edge devices	Not as effective at filtering ATE or RTE Without a properly defined physics loss, it devolves into its naïve base model	Requires additional information to handle unpaired data, but is designed for physical plausibility, and adaptability.
ADNet(8)	Consists of 4 down sampling and 4 upsampling layers The encoder connects to the decoder through the CAT module. with an intermediate module the MTHA	Enhances feature extraction Accelerates convergence	Requires paired clean-noisy data Potential for noise if attention mechanism not propemed slightly worse ataset Not-real time	The only model covered that requires paired data, it is designed for reducing signal distortion, and fast convergence without pre-training.
KNN(9)	K nearest Neighbors algorithm averages k previous similar signals	Ease of implementation Non-parametric Adaptable, possible real-time application	Real time capabilities depend on dataset size and optimization Sensitive to outliers High time complexity	The only model covered that has not been validated on dynamic datasets. Contrary to the rest, it does not require training data, and is efficient on some parameters

EVALUATION METRICS AND BENCHMARKING

First, numerous different metrics were used in papers discussing accelerometer denoising, as shown in Table 3. PILOT and ADNet share the same metric of using MSE and MAE to evaluate performance. Additionally, PILOT goes further to determine the downstream denoising effect of using a localization algorithm, such as IONet, to determine position. Conversely, HEROS-GAN uses Allan variance instead as a metric for random errors. HEROS-GAN even proposes new metrics, such as CSRE and ZVRE, which capture information about range extensions (6). Meanwhile, ADNet and KNN use (Signal to Noise Ratio) SNR and (Peak Signal to Noise Ratio) PSNR for measuring the denoising effect. This may be particularly useful in low-dynamic or stationary conditions, as shown in the experimental results of (9). By addressing the process of downstream denoising effect in localization problems, PILOT's methodology has a clear advantage over what is demonstrated in (6, 8, 9) in terms of its physical plausibility and applicability for mobile robot localization (7).

Due to the variety of datasets and metrics used across papers, direct performance comparison remains limited (Table 4). For example, even though PILOT and ADNet both use MAE and MSE, the models were trained and evaluated on different datasets under different conditions (7, 8). In the case of PILOT, it is used to judge the physics alignment of the denoised signal and is not a direct comparison between the denoised signal and the raw signal (7). ADNet, on the other hand, does utilize a direct comparison between the raw signal and the denoised signal (8). In Table 1, it is shown that the metrics used by HEROS-GAN and PILOT relate to the usage of unpaired data, as well as the model's task. HEROS-GAN and PILOT both use metrics to demonstrate physical plausibility in different ways. While HEROS-GAN focuses on over-range signal reconstruction and measuring drift through the ZVRE metric, PILOT uses downstream dead-reckoning performance metrics to verify physical plausibility.

In contrast to papers focusing on accelerometer denoising, there is consistency between papers discussing robot localization and dead reckoning. Most use ATE, RTE, and RRE for position and orientation, respectively (10-13). Though it is clear that the scope and primary concern of accelerometer denoising papers often do not require experimental data for position errors, it would be extremely helpful if position-based error metrics were provided to judge the applicability of such algorithms for localization. Particularly when using metrics such as ATE and RTE, which are commonly used for determining localization performance.

Table 3. Evaluation metrics reported in accelerometer denoising studies

Metric	HEROS-GAN (6)	PILOT (7)	ADNet (8)	kNN (9)
CSRE	√			
ZVRE	√			
Allan Variance	√			
MSE		√	√	
MAE		√	√	√
RMSE			√	√
SNR			√	(PSNR)
ATE		√		
RTE/RRE		√		
Huber loss			√	

Metrics are grouped by error domain (e.g., trajectory accuracy, signal reconstruction quality, range extension) and indicate which studies applied them.

Table 4. Definitions and calculation methods for evaluation metrics used in accelerometer denoising

Abbreviation	Name	Description
CSRE	Clipped Signal Reconstruction Error	Calculated as an RMSE between clipped high-cost sensor data and reconstructed sensor data (6)
ZVRE	Zero-Velocity Residual Error	Calculated as the absolute value of the integral of acceleration data over a time period T for stationary signals (6)
Allan Variance	Allan Variance	A time domain technique to analyze quantization noise, velocity random walk noise, and bias instability (6)
MSE	Mean Square Error	Average of the squared difference between denoised data and clean data (8)
MAE	Mean Absolute Error	Average of the absolute value of the difference between denoised data and clean data (8)
RMSE	Root Mean Square Error	Average of the square root of the squared difference between denoised data and clean data (8)
SNR	Signal Noise Ratio	Ratio of the strength of the signal to the strength of the noise (8)
PSNR	Peak Signal Noise Ratio	Ratio of the maximum strength of the signal to the strength of the noise (9)
ATE	Absolute Trajectory Error	The RMSE over the entire location estimate versus the ground truth location trajectory (7)
RTE/RRE	Relative Translational/ Rotational Error	RMSE of location estimates versus the ground truth location trajectory over a fixed time interval (7)

Abbreviations are expanded and formulas summarized to provide a consistent reference for interpreting reported results.

CHALLENGES AND CONSTRAINTS IN ACCELEROMETER DENOISING

Range Extension and Over-Range Signal Reconstruction

Overall, little research has been conducted in the areas of range extension for low-cost IMUs. Of the studies reviewed, HEROS-GAN shows the most promise for the field of range extension for low-cost IMUs. The premise of CSRE is extremely useful because it offers insight into how certain ranges of the signal behave, rather than a total summation over all parts of the signal (6). By exclusively summing over the parts of the signal that have been "clipped", it isolates over-range regions, helping assess denoising performance in areas where traditional error metrics are less informative. This is important because their algorithm effectively generates new signals outside the operating range of the low-cost sensor. When a measurement exceeds the sensor's maximum range, motion information is essentially lost, and the graph of acceleration data shows a flat line. In terms of dead reckoning, this represents a smaller change in velocity during sharp turns, which causes large errors when integrating for position.

For example, if the robot were to travel in a circle, the centripetal acceleration would be measured less than the true value, thus leading to tracking a larger circle than is travelled. Another example is in linear motion, if there were a sudden stop or collision, the positioning system still believes the robot to be moving forward, even when it is stopped. This study also provides a valuable metric, the ZVRE. It represents the drift of the accelerometer over a time period by integrating the acceleration over time and comparing the start and end velocities (6). It provides more detailed insight into the drift of an accelerometer over time and its impact on velocity. Consequently, a hypothetical new metric could be used such that the acceleration is integrated twice, yielding its drift in position over time. This is useful if the robot travels at approximately constant velocity and the change in position deviates due to noise in the accelerometer. By isolating and providing a direct comparison of position estimates, it could be used to analyze the effectiveness of tracking when following a motion profile or other similarly predictable trajectory.

Training Data Requirements and Scalability

Referring to Table 1, HEROS-GAN and PILOT describe methods to alleviate the need for paired data through special mechanisms. Meanwhile, ADNet specifically requires the use of paired data for accelerometer denoising. By addressing the problem of utilizing unpaired data for accelerometer denoising, methods such as HEROS-GAN and PILOT have notable advantages over methods that require paired training data for practical applications. At the same time, the kNN method allows for potentially the best usage in real-time scenarios, because it does not require training data at all. However, kNN-based methods may not be as scalable as HEROS-GAN and PILOT due to their high time complexity and potentially more training parameters (9).

As described in Table 5, HEROS-GAN and PILOT

Table 5. Training data requirements and strategies across reviewed denoising methods

Algorithm	Training Data Requirements	Training Method	Stationary	Dynamic
HEROS-GAN (6)	Accelerometer data	This method addresses the lack of ramewise paired training data, by sing custom loss functions to xploit similar features between high nd low cost sensor signals	√	√
PILOT (7)	Accelerometer data Additional positional, other hysically related data for training	This method addresses the lack of ramewise paired training data, by nforcing physics based loss unctions, to increase physical lausibility	√	√
ADNet (8)	Accelerometer data	This method requires paired training ata, as well as a relatively complex raining phase.	√	√
kNN (9)	No training phase	This method addresses the lack of ramewise paired training data, by ot utilizing a training phase. It irectly predicts the result during untime.	√	

The table outlines whether paired or unpaired data were needed, the approaches used to overcome data scarcity, and the model's testing conditions (stationary vs. dynamic datasets).

are different approaches for using unpaired training data. Specifically, HEROS-GAN does not require additional information from other sensors but leverages custom loss functions to aid training. The benefit of this is that it is easier to acquire only accelerometer data during training, and acquiring position data would require the technologies mentioned in (1). A disadvantage of HEROS-GAN is that it may be more difficult to verify the physical plausibility of the model in training. This would require special tuning of the OTS loss function to ensure the correct features are learned. An advantage of PILOT is that it is designed for physical plausibility, at the sacrifice of requiring additional training data and sensors.

APPLICATIONS TO MOBILE ROBOT DEAD RECKONING

The papers focusing on the localization of mobile robots implemented in real-time rely on a combination of Kalman filters (10) and wheel odometry to complement accelerometers (11). Even with sophisticated accelerometer denoising, the cubic nature of position drift due to integrating acceleration renders even accurate inertial sensors unreliable for dead-reckoning applications (12). For this reason, approaches for real-time localization focus on sensor fusion to alleviate the need for more precise accelerometer data. An example of this is mentioned in Brossard, where researchers filter odometer data first before feeding it into an Extended Kalman Filter to fuse it with accelerometer data, focusing more on more predictable wheel odometry to compensate for IMU drift (11). Others, such as IONet, attempt to learn velocity information from accelerometer data to prevent accelerometer error accumulation (12). Overall, the reliance on low-cost MEMS IMUs for mobile robot dead-reckoning is underrepresented in research.

Similar to the logic behind ZVRE, a method named ZUPT (Zero Velocity Update) exists and is used in pedestrian tracking systems to correct for accelerometer drift. ZUPT works by resetting the velocity to zero based on when the foot contacts the ground. The motivation behind this is that there are periodic, known times when the velocity is zero, and velocity measurements can be reset to help mitigate drift (12). In a hypothetical alternative method, if a preplanned path is used, such as one based on a motion profile, there are times when the velocity is known to be zero or constant. The position could then be filtered in two ways, similar to PILOT for constant velocity, or like ZUPT for pedestrians when standing still. For all of the above hypothetical methods, a metric for position error based on constant velocity provides important information on the characteristics of accelerometer drift. Typically, as stated in some papers on mobile robot localization, wheel odometer data is used to complement accelerometer data and prevent drift (11). However, in some situations, no other sensors are available, which creates the necessity for well-planned paths and reset points to apply ZUPT and mitigate drift.

While kNN and ADNet perform well on stationary signal denoising, HEROS-GAN and PILOT propose methods of handling dynamic processes. In particular, HEROS-GAN addresses problems due to sudden changes in motion with its over-range reconstruction capabilities. Similarly, PILOT addresses the physical plausibility of reconstructed signals through its use of a physics loss. A potential direction of research could be to use a physics-based verification method for over-range signal reconstructions, either through the use of a loss function or hard constraints. Based on the methods currently available, HEROS-GAN and PILOT may have more advantages than kNN and ADNet in dynamic situations. This is not to say that kNN and ADNet should not be used for mobile robot dead-reckoning. On the contrary, a potential application is using kNN due to its low computation and training time for short stationary signal denoising, while applying a PILOT or GAN architecture during dynamic situations to gain the benefits of both. This is especially useful during routines where there are pauses or regions of constant velocity when robots perform tasks, providing a potential augmentation to ZUPT.

CONCLUSION

The examined methods of accelerometer denoising have numerous potential applications and areas of further research. General metrics for accelerometer error, including MSE, MAE, and SNR, help broadly evaluate the performance of accelerometer denoising techniques. Meanwhile, other metrics, such as CSRE and ZVRE, could specifically judge aspects of signal reconstruction and over-range reconstruction. Overall, there is a lack of unified evaluation metrics, often stemming from specialized training architectures and tasks. There are gaps in research for accelerometer denoising in areas such as range extension and inertial-only tracking for non-periodic motions. In addition, further research could focus on making deep-learning-based accelerometer denoising algorithms more computationally efficient and effective using unpaired data in real-time signal processing. Sensor fusion algorithms of wheeled odometers and denoised accelerometers represent potential real-world applications of deep learning accelerometer denoising methods. In particular, Kalman filter variants could be used to fuse two or more sensors for even more accuracy and reliability in dynamic conditions. Research could explore combinations of different deep learning algorithms for multiple phases of motion. A limitation of the study is that this field is relatively new. Quantitative cross-comparison of models is limited in this study due to differences in evaluation metrics. As more specialized algorithms are developed for different use cases, it becomes increasingly pressing to develop unified performance metrics, training datasets, and evaluation techniques.

This paper provides a review of modern deep learning models: GANs, kNNs, Wave-U-Nets, and physics-informed networks, as well as improvements made by researchers for mobile robot accelerometer-based dead-reckoning algorithms. This paper reveals that several localization algorithms rely on sensors such as vision, GPS, or wheel odometry because they are more stable. However, this doesn't work in all situations, and there's a gap in research for accelerometer-based positioning algorithms. Overall, deep learning as a method for filtering accelerometer data is a growing field, and research is particularly promising for range extension using generative models or physics-informed networks.

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CONFLICT OF INTERESTS

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