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SURVEY

Advancements in UWB-Based Human Motion Detection Through Wall: A Comprehensive Analysis

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ABSTRACT Ultra-wide Band (UWB) technology has emerged as a pivotal tool for human motion detection, finding applications in diverse areas ranging from smart homes to automotive safety. This paper presents a comprehensive survey of methodologies employed in UWB-based motion detection, elucidating their strengths, challenges, and performance metrics. While several methods, including Convolutional Neural Network (CNN) approaches, have been explored, challenges such as motion state overlaps, the necessity for enhanced spatial resolution, and background noise interference persist. Among the various methods analyzed, the SGWO-based RMDL technique emerges as a frontrunner, offering superior accuracy, reduced mean squared error, and impressive true negative and positive rates. Moreover, its computational efficiency sets a precedent in human motion detection. This paper provides insights into the state-of-the-art Through the wall imaging and human vital signs observation for future research and realtime applications.

INDEX TERMS Ultra-wide band (UWB), human motion detection, CNN, SGWO-based RMDL, motion classification, accuracy, TPR, TNR, MSE, deep learning.

I. INTRODUCTION

Integrating Through-the-Wall Radar (TWR) technology with Impulse Radio Ultra-Wideband (IR-UWB) signaling represents a notable advancement in remote sensing, particularly in scenarios requiring the detection and localization of objects or individuals behind obstacles. IR-UWB RADAR, characterized by its extensive bandwidth and unique signaling characteristics, has been reinvigorated in the technological landscape following its legalization by the Federal Communications Commission (FCC) in 2002 [11].

IR-UWB RADAR is primarily known for its Impulse Radio UWB (IR-UWB) signalling, which leverages very short baseband pulses, typically in the nanosecond range, to occupy a vast bandwidth in the frequency domain. The simplicity of IR-UWB transmitters, which often do not require intricate RF circuitry for up-conversion or filtering, and their innate ability to generate short pulses has been a driving factor behind their adoption [10].

One of the most significant applications of IR-UWB RADAR lies in TWR technology. These radars utilize the penetrating capabilities of low-frequency electromagnetic waves, which are inherent in the UWB technology, to detect human targets behind walls. This feature is invaluable in urban combat, anti-terrorism operations, disaster rescues, criminal investigations, and search and rescue operations [1]. The intense penetration capabilities of UWB, coupled with its high-range resolution, position it as an ideal tool for these critical applications. The broader frequency range of the transferred impulse in UWB can even mitigate radar blind spots, enhancing its efficacy [40].

Figure 1 illustrates the experiment conducted by Pardhu and Kumar [45], [46] on through-the-wall imaging, demonstrating the process of identifying objects concealed behind a wall.

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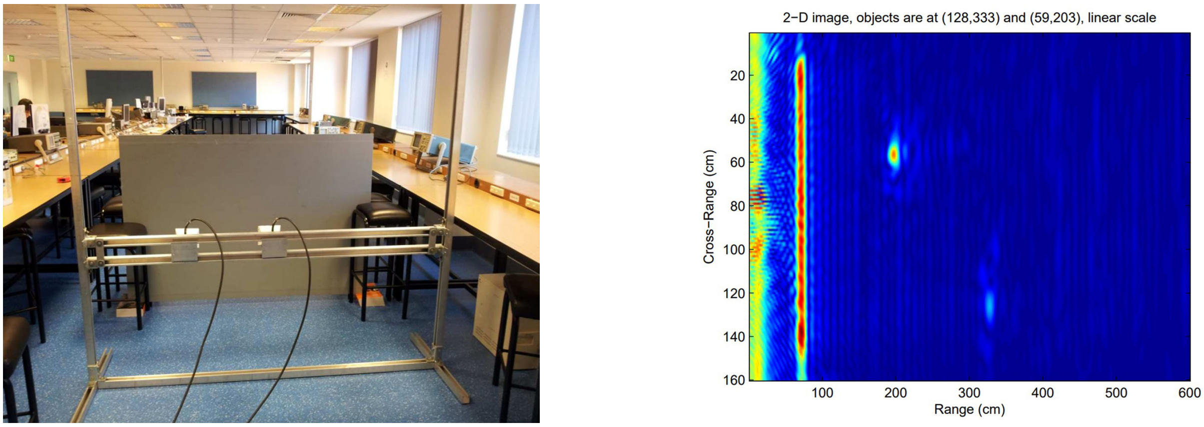

(a) (b)

FIGURE 1. (a) Through the wall imaging experimental setup with 1 wall (b) Result of the particular experiment.

Moreover, IR-UWB RADARs offer non-invasive monitoring solutions, a significant advantage in a world increasingly concerned with privacy. Their ability to detect and categorize human motion behind walls without compromising individual privacy sets them apart from other technologies like infrared, visible light, and acoustics [13], [40]. This has led to their use in post-disaster rescues, non-contact life monitoring, anti-terrorism operations, and even smart home applications, where their integration can lead to more responsive and intuitive living environments [40].

Figure 2 depicts the real-time experiment conducted by Thottempudi and Kumar [42], showcasing the use of SFCW RADAR to identify human targets and detect vital signs behind walls.

Figure 2(b) showcases the outcome of a real-time experiment aimed at identifying human targets concealed by a wall, utilizing SFCW (Stepped Frequency Continuous Wave) RADAR technology. The image depicted in Figure 2(b) represents the processed radar returns, where distinct patterns can be observed as a result of human movement behind the obstruction.

In the radar image, the human being signal is characterized by a series of concentrated, high-intensity reflections that stand out against the background noise and static reflections from the wall. These reflections are a result of the radar waves being bounced back from the moving human target, capturing dynamic changes over time.

A. KEY FEATURES OF THE HUMAN SIGNAL

- **Location and Movement:** The position of the human target is indicated by the aggregation of bright spots, which correspond to the radar cross-section enhancements caused by human motion. The trajectory or movement pattern of the person can be inferred from the variation in these bright spots over sequential radar scans.
- **Signal Characteristics:**Compared to static objects, the human being signal exhibits a dynamic nature, with fluctuations in intensity and position reflecting different motion states such as walking, waving, or other gestures.
- **Signal-to-Noise Ratio (SNR):** The human being signal is discernible from the background primarily due to the higher SNR in areas of motion. This contrast is achieved through advanced signal processing techniques that suppress background clutter and enhance the motion signal.

The integration of Artificial Intelligence (AI) and Machine Learning (ML) has improved the capabilities of IR-UWB RADAR tremendously. The best performance for target identification through the wall has been found via Convolutional Neural Network (CNN) using data from IR-UWB RADAR [29], [40]. Machine learning techniques such as support vector machines (SVM) and deep learning models are widely known to be the best for handling sophisticated data environments [1], [2], [3], [4], [5], [6], [7], [8], [9]. Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) are conceived as competent methods applied for the optimization of complexities in tracking human motion through the wall [15]. Identifying and classifying human motion through the wall using IR-UWB RADAR is the focus of the current research. Pardhu and Kumar [41] proposed that this approach will involve a new human motion classification through wall problem formulation as a hybrid optimization algorithm development using training on a Random Multimodal Deep Learning Classifier. This method combines the features of UWB Signals and novel AI Algorithms to achieve better accuracy and lower computational time in classifying human motion through the wall. This research has diverse applications in smart home development, defense applications, and disaster management [47]. Figure 3 illustrates the real-time experiment conducted by Pardhu and Kumar [41] to classify human movements through a wall.

The IR-UWB RADAR utilizes advanced computing technology and possesses distinctive attributes, making it a pioneering force in revolutionizing the identification and analysis of human movement through the wall. The outlined process is vital in the evolution of technology as it enables

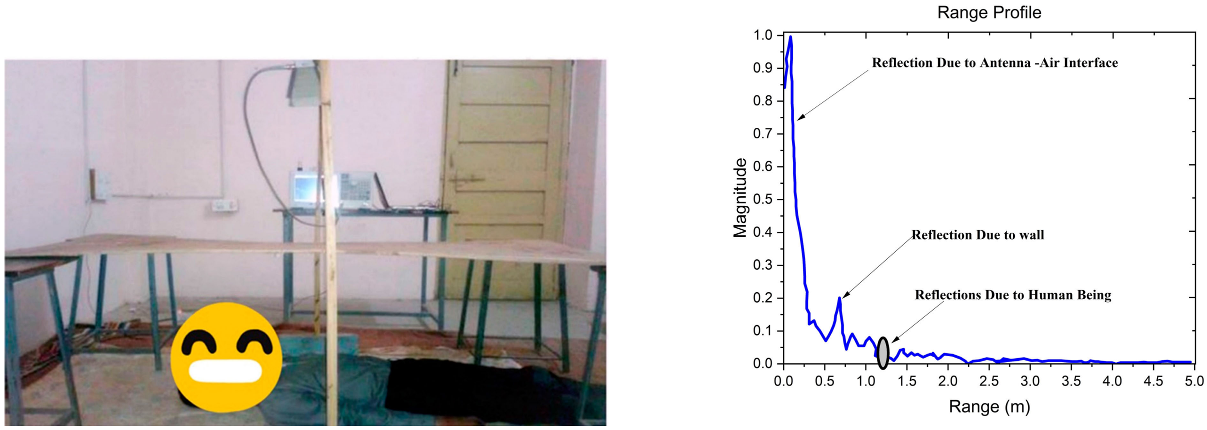

FIGURE 2. (a) Human target identification experiment setup in real-time Concealed by the wall, (b) Experiment's outcome.

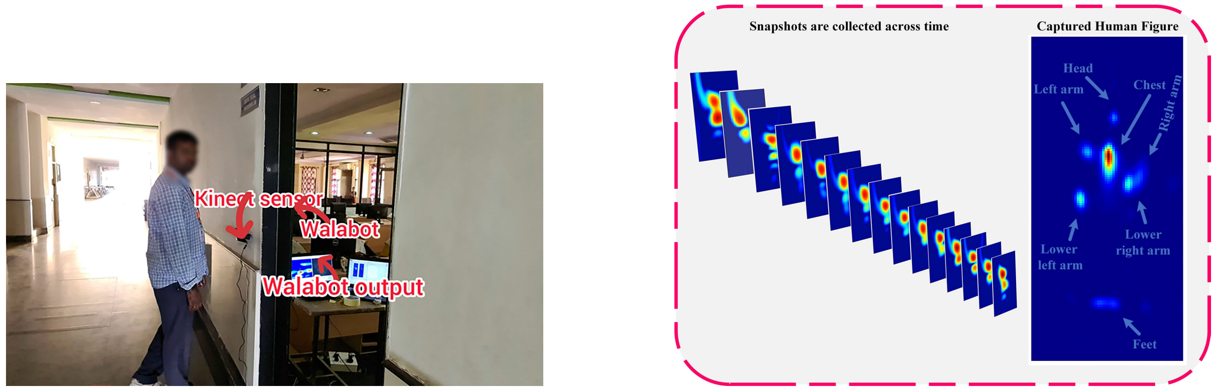

FIGURE 3. (a) Realtime experiment, (b) Reconstruction of human structure from the snapshot received during the motion.

the shift from state-of-the-art technological solutions to those applied in the realtime [1], [6], [10], [11], [13], [15], [29], [40], [47].

II. LITERATURE ANALYSIS OF HUMAN MOTION ANALYSIS BEHIND WALL

A. HUMAN MOTION ANALYSIS USING MACHINE LEARNING ALGORITHMS

Integrating state-of-the-art radar technologies with artificial intelligence constitutes a significant step forward. Such a progression fundamentally lies far away from high frequencies and closer to low frequencies - between 1 and 3 GHz, influenced by the critical research of V.C. Chen [68], [71]. As described in [68], [69], [78], [79], [80], and [81], this frequency band selection option avoids necessarily occurring signal attenuation and distortion during the propagation across various constructional materials. Implementing a radar system based on an ultra-wideband (UWB) within 400 MHz to 4.4 GHz is an explicit advancement. This system exhibits an outstanding range and resolution characteristics, essential for offering precise and exemplary surveillance by elderly care applications.

An ultra-wideband (UWB) radar system is characterized by a unique time-dependent signal function, $s(t)$, which presents excellent resolution essential for correct motion detection. The key to this system is how Robust Principal Component Analysis (RPCA) is ingrained within it for signal processing purposes. Whereas the RPCA method accurately decomposes X into a low-rank matrix L and a sparse matrix S by $X = L + S$. There exist several works in the envisaged area [71], [72], [73], [74], [75], [76], [77], [82] on this decomposition technique. Further, the UWB radar system uses a new technique, the Range-Max Time-Frequency Representation (R- max TFR), for outputs of signal enhancement purposes.In their study, Gao et al. [47] developed an innovative approach by integrating Through-the-wall radar (TWR) with a multilink auto-encoding neural network, creating the TWR-MCAE technique. This technique aimed to refine the accuracy of human motion detection, particularly in scenarios where walls act as obstructions. The TWR-MCAE model was modified to improve the detection of sparse motion features prevalent in human movements and eliminate interference from wall debris, which typically led to inaccurate motion detection. Although this model made great efforts to find motion sparsity features, it ultimately imposed limitations on them. One significant deficiency was the absence of optimization techniques, which have the potential to improve the performance of the model significantly.

Mathematically, the R-max TFR is given as R-max $\text{TFR}(t,f) = \max_\tau(|S(t,\tau,f)|)$. This enhancement method significantly enhances signal clarity in environments with more complex data [68], [69]. Kiliç et al. [1] take it to the next level by classifying human postures. It uses Convolutional Neural Networks (CNN) along with Through-the-Wall Radar (TWR), where it uses Stepped Frequency Continuous Wave (SFCW) radar. The mathematical expression for the SFCW radar is given by $s(t) = \sum_{n=1}^{N} e^{j2\pi(f_0+n\Delta f)t}$, where f_0 is the initial frequency, Δf represents the frequency increment, and N denotes the total number of frequency increments. CNNs are represented mathematically as a series of convolution operations $F^{(l)} = \sigma(W^{(l)} * X + b^{(l)})$. They improve the system's ability to differentiate between individuals' spatial locations and orientations, even when obstructed by walls [1].

The Impulse Radio Ultra-wideband (IR-UWB) technology, pivotal in both civil and military sectors for its ability to penetrate non-metallic and non-transparent barriers, is defined by a broad frequency spectrum (3.1 to 10.6 GHz) and a signal comprised of short pulses ($s(t) = \sum_{n=-\infty}^{\infty} p(t - nT_f)$). This technology is ideal for applications such as post-disaster rescue [84], counter-terrorism [32], [85], and non-contact life monitoring [39], [86], outperforming visible light and infrared technologies in adaptability and privacy [13]. Advances in AI have greatly enhanced UWB radar's target detection accuracy, with machine learning techniques like Support Vector Machines (SVM), formulated as an optimization problem (min $\frac{1}{2}\|\mathbf{w}\|^2$ subject to $y_i(\mathbf{w} \cdot \mathbf{x}_i + b) \geq 1$) [87], playing a crucial role. Additional methods include multiscale residual attention networks [88] and feature extraction techniques like discrete wavelet transform ($X(a,b) = \int x(t)\frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right) dt$) [89], [90], [91]. Techniques such as PCA for data dimensionality reduction [92], CARTFR, and MHHT for activity recognition [26], [93], and segmented convolutional gated recurrent neural networks for human activity recognition [94] further demonstrate the sophistication of these systems. Despite advancements, challenges like limited radar target datasets [95] persist, addressed through transfer learning [96], [97] and small sample learning [98], [99]. Zhengliang et al.'s development of an IR-UWB dataset for human motion states [40] marks a significant step, albeit with limitations in low-frequency human data capture, indicating potential areas for future enhancements in security and smart environment
applications.

B. MIMO RADAR BASED HUMAN MOTION DETECTION

Modern radar systems have experienced significant evolution, particularly with the advent of Synthetic Aperture Radar (SAR) and Multi-Input-Multi-Output (MIMO) technologies, which have substantially surpassed traditional monostatic radar capabilities in generating high-resolution 2D and 3D imagery for a variety of applications. Using a single transmitting and receiving antenna, SAR achieves high azimuth resolution. This attribute has proven beneficial for applications such as ground penetrating radar (GPR) and various vehicular and airborne operations [100], [101], [102], [103]. The principle underlying SAR can be mathematically described by the radar equation for SAR, which is:

$$\text{SAR}(x, y) = \int\int s(t, \alpha)\, e^{-j\frac{4\pi R(x,y,\alpha)}{\lambda}}\, dt\; d\alpha \tag{1}$$

where $s(t, \alpha)$ represents the signal at time t and antenna position α, and $R(x, y, \alpha)$ denotes the range from the antenna to the point (x, y) on the ground.

In contrast, MIMO technology, which utilizes multiple antennas for transmitting and receiving, provides enhanced resolution. However, this setup results in delayed data acquisition, a challenge particularly observable in applications like breast cancer diagnosis and concealed weapon detection [104], [105], [106], [107], [108], [109], [110], [111], [112], [113], [114]. The mathematical representation of a MIMO radar system can be expressed as:

$$\text{MIMO}(t, r) = \sum_{i=1}^{N_t}\sum_{j=1}^{N_r} s_{ij}(t)\, e^{-j2\pi f_{ij}(t) r} \tag{2}$$

where N_t and N_r are the numbers of transmitting and receiving antennas respectively, $s_{ij}(t)$ is the signal transmitted by the i-th transmitter and received by the j-th receiver, and $f_{ij}(t)$ is the corresponding frequency.

S-band UWB switched-antenna-array radar with superior performance has also been proposed to reduce the complexity and cost brought in by MIMO systems through scaling down from a 13-Tx/8-Rx to a 1-Tx/5-Rx structure [115], [116], [117], [118]. It is specifically designed to detect human positions behind concrete walls, and therefore, the system is best suited to critical applications such as hostage rescue. The operating procedure of this system transmits UWB signals and captures the reflected signals, which are subsequently subjected to preprocessing and transformed from 3D arrays to 2D arrays by statistical variance analysis. Subsequently, the image is reconstructed by back-projection employing a Sinc filter.

Mathematically reconstructed through a back-projected algorithmic, the process can be represented as follows:

$$\text{Image}(x, y) = \sum_{n=1}^{N} \text{Sinc}\left(\sqrt{(x - x_n)^2 + (y - y_n)^2}\right) V_n \tag{3}$$

where N is the number of antenna elements, (x_n, y_n) are the coordinates of the n-th element, and V_n is the variance analyzed signal at that element.

Complementing these developments, Rittiplang and Phasukkit [27] introduced a through-wall S-band UWB radar with a switched antenna array, focusing on detecting stationary subjects via respiration analysis. Despite its effectiveness, this system lacks specific functionalities required for comprehensive rescue operations in disaster scenarios, highlighting the potential for further advancements in emergency response technologies.Zhang et al. [48] proposed an innovative way through the development of TwSense to develop an innovative Through-the-wall detection system with a commercial Wi-Fi device. It had features different from traditional means and concentrated on alleviating the efficiency and robustness of detection. TwSense had been unique for this system in that its lesser processing time and increased robustness were likely to make it highly suitable for real-time applications. Despite its extensive features, the system had a significant drawback: it required including the Fresnel zone model in its through-the-wall detection methodology.

This omission means that TwSense, while effective in certain aspects, needs a comprehensive theoretical framework that fully integrates the dynamics of human activity with wireless signal behavior. The absence of such a model indicates potential areas for further development and refinement in the system. This suggests additional research could lead to a more holistic and theoretically grounded approach to through-the-wall detection technology.

Recent advancements in radar technology have been significantly influenced by Narayanan et al. [23], who developed a multi-frequency radar model specifically designed for human detection and activity classification, focusing on short-range applications. This model, particularly adept in through-wall detection scenarios, operates within the S-Band frequency spectrum and utilizes two distinct waveforms, selected through specific switching mechanisms and incorporating wide-band noise waveforms. Despite its innovative approach, the model faces limitations in detecting certain human activities, revealing opportunities for enhancement to ensure more comprehensive detection, crucial for security, surveillance, and rescue operations. The importance of such technology is underlined in military and law enforcement contexts, where detecting human targets and movements through walls and light foliage is increasingly vital [23]. For example, low-frequency microwave signals (less than 5 GHz) can penetrate building walls with relatively low loss, and at short ranges (typically 6–10 feet), portable antennas with wider beamwidths can isolate a single human. The antenna beamwidth θ of a circular aperture antenna is given by $\theta = \frac{1.27\lambda}{D}$ for a single-way beamwidth [119], where λ is the wavelength and D is the antenna size. Considering the two-way beamwidth needed for radar applications, θ becomes $\theta = \frac{1.27\lambda}{D\sqrt{2}}$ [119]. For instance, at a 3 GHz frequency in the S-Band (2–4 GHz), corresponding to a wavelength of 10 cm, and with a 6-inch antenna, the two-way beamwidth is about 34.2 degrees. The azimuth or cross range resolution ΔR_{CR} for a real-aperture radar is given by $\Delta R_{CR} = R\theta$ [119], which at a range of 2 meters yields an adequate resolution of approximately 1.1 meters for isolating a single human. Moreover, the down-range resolution ΔR_{DR}, determined by the transmit bandwidth B, is expressed as $\Delta R_{DR} = \frac{c}{2B}$ [120], [121], where c is the speed of light. These mathematical analyses demonstrate the capability of radar systems to adapt to various operational requirements, highlighting the potential for future enhancements in human detection through barriers.

Recent advancements in radar technology, particularly in human motion detection, have been notably propelled by the work of Wang et al. [36], who introduced a significant innovation with their residual subspace projection method. Utilizing compressed sensing techniques, this method efficiently collects Ultra-Wideband (UWB) radar data and has shown effectiveness in detecting various human motion states. Within the S-Band frequency spectrum, up to 3.5 GHz, UWB radar is recognized for penetration capabilities through common obstructions like walls, making it ideal for through-wall security, rescue, and surveillance applications. Despite its effectiveness, Wang et al.'s method revealed a critical limitation in accurately classifying specific types of human movements. Addressing this gap by refining the classification process could substantially improve the method's accuracy, enhancing its utility in a wider range of applications [9], [12], [16], [31], [122], [123], [124].

A key aspect of these advancements is the mathematical processing of radar signals. The Fourier transform, for instance, plays a crucial role and is mathematically expressed as $F(\omega) = \int_{-\infty}^{\infty} f(t)e^{-j\omega t}dt$, which transforms time-domain signals into their frequency domain representations [125], [126]. Additionally, singular value decomposition, instrumental in processing compressed UWB data, involves decomposing a matrix A into its constituent matrices, formulated as $A = U\Sigma V^*$, with V^* being the conjugate transpose of V [20], [127], [128], [129], [130]. These mathematical techniques are pivotal in enhancing the radar's capability to detect and classify human movements, even through barriers, making significant contributions to security and emergency response.

Recent ultrawideband (UWB) radar technology advancements have significantly enhanced the ability to detect obscured human activities in complex environments, such as through walls or underground [131]. A prominent area of focus is identifying vital signs and movements of human targets, where techniques like the fast Fourier transform (FFT) and S-transform have been instrumental. Li et al. [20] employed these methods to extract respiration frequencies and locate static human targets. In contrast, Wang et al. [34] focused on imaging moving targets, where the complexity of the task increases due to environmental interference and the coupling of movement with vital signs. The time-domain finite element method (TDFEM) has been proposed to simulate radar data for moving humans, categorizing human movements into long-range and periodic motions like respiration. In this context, the mathematical formulation for radar signal processing, particularly for movement, can involve models like $x(t) = A(t)\cos(2\pi f_c t + \phi(t))$, where $x(t)$ is the radar signal, $A(t)$ the amplitude, f_c the carrier frequency, and $\phi(t)$ the phase shift caused by movement [132].

In signal processing, the UWB single-input multiple-outputs (SIMO) radar system was used to reconstruct paths and associate this to vital signs in the radar images. Methods like empirical mode decomposition (EMD) and multivariate empirical mode decomposition (MEMD) [132], [133], [134] have been used for the processing of SIMO radar data for extracting vital signs from multi-channel, complex signals. For example, the MEMD decomposes a multichannel signal into a set of intrinsic mode functions (IMFs) which can be mathematically expressed as $X_i(t) = \sum_{j=1}^{n} IMF_{ij}(t)$, where $X_i(t)$ is the ith channel signal and $IMF_{ij}(t)$ the jth IMF of that channel. This decomposition aids in isolating vital signs from other signal components. On the other hand, Wei and Zhang et al. [37] used TDFEM to mimic radar data akin to those produced by human respiration while making background removal techniques for better analysis of the data required more empirical validation before determining its efficacy in real-world applications. This gap underscores the need for tests in actual life to prove the level of reliability these advanced radar models make in executing some of these critical applications, such as security and emergency response.

Saeed et al. [28] have taken a commendable step ahead in human behavior detection radar technology by ingeniously combining Convolutional Neural Networks (CNN) with the Kalman filter (KF). This approach aims to generate accurate feature maps and use radar data in privacy-preserving ways across various scenarios. Despite the innovation in design, the method needs more optimization in learning from each convolution layer's kernel, which is a shortfall that presents an opportunity for enhancing the learning mechanism towards a better version for detection and classification accuracy. This work is put in a broader research context about monitoring human behaviors through radar sensors. UWB systems have been studied for their intrinsic capabilities for other scenarios, such as anomaly detection [135], [136], [137], [138], [139], [140]. Long-distance detection capabilities and penetration potential of UWB radar sensors make them particularly suitable for this whenever an area needs human motion detection and identification in any weather conditions and at any time conditions [141], [142], [143], [144], [145]. Such systems often utilize micro-Doppler (MD) signatures, which mathematically can be described by the Doppler shift formula $\Delta f = \frac{2v}{c} f_0$ where Δf is frequency shift, v is the target's velocity, c is the speed of light, and f_0 is the original transmitted frequency. This Doppler shift is crucial for classifying and recognizing moving objects [12], [13]. With KF and CNN fused, which reached a detection rate of 98.7% even in complex scenarios with barriers, Saeed et al.'s approach shows enormous promise in practical applicability yet points to further empirical validation and optimization [28].

C. HYBRID OPTIMIZATION ALGORITHMS-BASED HUMAN MOTION CLASSIFICATION

Pardhu and Kumar [41] have made efforts in the direction of improving human motion detection by proposing the use of the *Spotted Grey Wolf Optimizer (SGWO)* as a novel hybrid algorithm that synergistically combines both the Spotted Hyena and the Grey Wolf Optimizer. In this work, the SGWO has been used to improve the performance of the *Random Multimodal Deep Learning (RMDL) Classifier* in human motion classification, such as walking and standing, with great accuracy, especially in complex background conditions such as presence detection behind walls. The SGWO algorithm, inspired by the intricate social hierarchy and collaborative hunting strategies of hyenas and grey wolves, is adept at solving various complex optimization challenges encountered in motion detection. Mathematically, the SGWO algorithm can be expressed as an expression that models the agents' behavior and position updates (hyenas and wolves). The new agent position is then obtained from the updating position formula as $x_{\text{new}} = x_{\text{old}} + A \cdot D$, where x_{old} and x_{new} represent the old and new positions of the agent, respectively, and A represents the coefficient matrix that describes both the direction and magnitude of step.

In contrast, D represents the calculated distance vector between the agent and the prey or target. This distance vector D is usually computed as $D = |C \cdot x_{\text{prey}} - x_{\text{old}}|$, where x_{prey} represents the prey position, and again, C is another coefficient matrix acting to define better the encircling behavior the agents adopt [41]. The application of SGWO in enhancing the effectiveness of the RMDL Classifier leverages the intense penetration and high range-resolution capabilities of UWB radar [6], [13], [32], [40]. UWB radar signal processing expertise of advanced methods such as the fast Fourier transform (FFT) [20], [37] for analyzing signals, and the back projection techniques [35], [37] for reconstructing an image from the radar data. Hence, a fusion of these advanced signal processing techniques into the SGWO-based RMDL Classifier avails accurate classification of the human movement required for various applications in security surveillance systems, search and rescue operations, and the development of intelligent home technologies [41].

Figure 4 presents a concise framework demonstrating the application of the Hybrid Spotted Grey Wolf Optimizer (SGWO) based Random Multimodal Deep Learning (RMDL) technique for detecting and classifying human motion behind walls. This framework details the process from the initial detection phase, utilizing SGWO's optimization, to the intricate classification phase achieved through RMDL's deep learning algorithms.

Ultrawideband (UWB) through-the-wall radar (TWR) systems, crucial in urban combat and search and rescue operations [147], confront challenges in human motion recognition due to wall-induced signal distortions such as attenuation and multipath effects [148]. These challenges necessitate enhanced data processing strategies for accurate

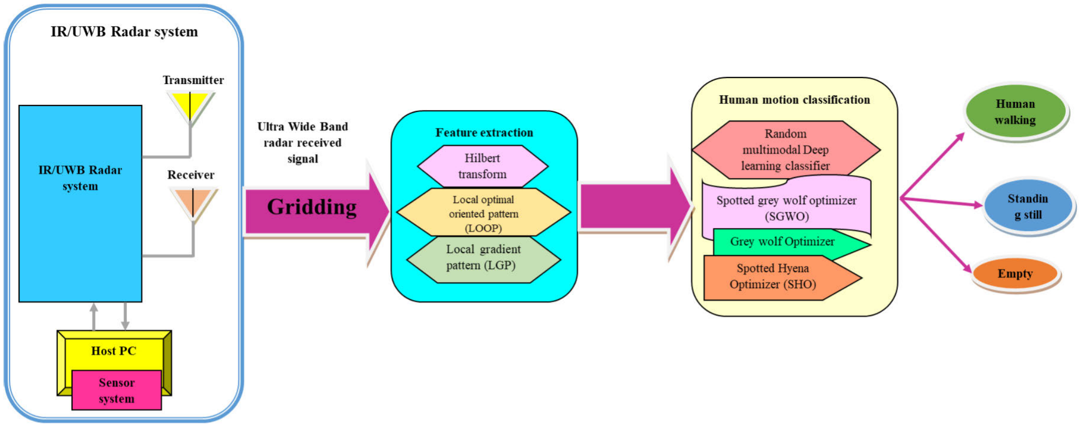

FIGURE 4. Framework for human motion classification based on SGWO based RMDL technique.

motion recognition. Initially reliant on classical signal processing methods for feature extraction and statistical classification [147], [148], [149], [150], [151], TWR systems have evolved to incorporate intelligent signal processing techniques. These include support vector machines (SVM) [152], time delay estimation methods [153], and orthogonal matching pursuit algorithms [154]. Despite improvements, these methods often struggle with complex motion data [2], [155]. Recent advancements leverage neural network approaches, such as convolutional neural networks (CNNs) [157] and autoencoder networks [156], offering superior feature extraction but at the cost of increased training time.

D. HUMAN MOTION ANALYSIS USING DEEP LEARNING ALGORITHMS

Addressing these limitations, a novel data augmentation method, the multilink convolutional autoencoding neural network (TWR-MCAE) [53], has been introduced. TWR-MCAE combines multiscale information in 2-D images with sparse and low-rank physical properties to enhance motion feature extraction in range-time and Doppler-time maps. Central to TWR-MCAE is the convolution operation, mathematically formulated as $F_{ij} = \sum_m \sum_n I_{m,n} \cdot K_{i-m,j-n}$ [53], where F_{ij} is the feature map, I the input, and K the kernel. This method significantly improves the classifiers' recognition accuracy and training efficiency, contributing to the advancement of UWB TWR technology in complex human motion detection scenarios.

In recent years, Ultrawideband (UWB) through-the-wall radar (TWR) technology has emerged as a key tool in indoor human monitoring, notably for applications like elderly care and gait recognition, owing to its non-contact nature and privacy preservation [157], [158]. Challenges in TWR, especially in through-wall detection, stem from signal distortions caused by wall interactions, leading to weakened micro-Doppler features [159]. Traditional enhancement methods like the Cross Ambiguity Function (CAF) generate micro-Doppler spectrograms by selecting columns with Doppler peaks from range-Doppler maps over time [83], [160], [161], [162], mathematically represented as $R_{max}(t, f) = \max(R(t, f))$, where $R(t, f)$ indicates range values for each time-frequency bin. Addressing further complexities such as interference from live conductive wires in walls, deep neural network approaches like conditional Generative Adversarial Networks (cGANs) have been adapted [163], [164], [165]. These networks transform wire-corrupted spectrograms into de-wired ones, as seen in the advancements by Wang, S., et al. with the Cycle-Consistent Generative Adversarial Network (Cycle GAN) incorporating identity loss for improved realism in spectrogram reconstructions [51]. However, integrating these advanced signal processing methods with various lightweight classifiers for enhanced efficacy in diverse detection scenarios remains a promising area for future exploration.

An et al. [51] utilized Robust Principal Component Analysis (RPCA) to eliminate stationary clutters from raw range slow-time maps. This method was particularly effective in reducing the multipath effects that often complicate time-frequency map analyses. The use of RPCA in this context marked a significant step in enhancing the clarity and accuracy of radar signal processing. However, a key challenge with this technique was its computational demand. The approach required many iterations to produce accurate results, translating to higher computational loads and longer processing times. While the method showed considerable promise in dealing with complex signal interferences, the need for a more efficient computational process indicates an area for potential improvement. Streamlining the RPCA process could lead to a more practical and faster implementation, making it more viable for real-time applications where rapid processing is crucial.

In the last two decades, the use of Ultrawideband (UWB) through-the-wall radar (TWR) for indoor human monitoring has become increasingly prevalent in fields such as counter-terrorism and law enforcement, especially in urban environments [166], [167], [168], [169], [170].

While optical and infrared sensors require a direct line of sight and are effective only in unobstructed areas, radar sensors exploit the ability of electromagnetic signals to penetrate walls, enabling the detection of humans within buildings [171], [172], [173], [174]. Though effective, active radar systems, utilizing wideband signals like impulse or Frequency Modulated Continuous Wave (FMCW) are often hindered by high costs and complexity [166], [167], [168], [169], [170]. In contrast, passive radar systems, which use existing signals from sources like WiFi networks, offer a more cost-effective and discreet alternative [175]. These systems, exemplified by Wi-Vi [176] and WiSee [177], have shown promise in detecting human motions through walls using WiFi signals. The Signal-to-Noise Ratio (SNR) of these detections, particularly for minor motions such as typing or breathing, can exceed 20dB after appropriate signal processing [162], [176], [177], [178], [179], [180], [181], [182], [183], [184], [185]. Mathematical analysis in passive radar often involves Doppler processing, where the Doppler shift $\Delta f = 2v/\lambda$ (with v being the velocity of the target and λ the wavelength of the WiFi signal) is crucial for detecting motion. Recent advancements have focused on enhancing the Doppler resolution using techniques like the Iterative Adaptive Approach (IAA) instead of traditional Fast Fourier Transform (FFT), allowing for better discrimination of micro-Doppler signatures [24]. Sun et al. [50] further developed WiFi passive radar models, optimizing deployment strategies to enhance surveillance capabilities. However, these models require refinement for more consistent performance across various scenarios.

In urban environments, particularly for counterterrorism and disaster rescue, detecting and locating concealed individuals, such as enemy personnel or victims behind obstacles, is crucial. Electromagnetic wave detection, especially ultrawideband (UWB) low-frequency signals, stands out due to its ability to penetrate different materials and maintain privacy [186], [187], [188]. While millimeter wave radar offers high distance resolution, symbolized by its fine range resolution $\Delta R = \frac{c}{2B}$ (where c is the speed of light and B is the bandwidth of the signal), it has limited penetration [189]. This leads to a focus on UWB low-frequency signals in TWR-based human action recognition. Advanced imaging techniques in TWR, such as the backprojection algorithm, are mathematically represented as $I(x, y) = \int S(t)\delta(t - \frac{2R}{c})dt$, where $I(x, y)$ is the image intensity, $S(t)$ the received signal, and R the range, have shown progress [34], [190], [191], [192], [193], [194], [195], [196]. However, these methods often require significant computational resources. In contrast, though suitable for real-time applications, parameter domain methods have limitations in scope [197], [198]. Addressing these, this paper introduces a network for simultaneous people counting, motion recognition, and static human localization, aiming to expand the practical applications of TWR. Lin et al. [52]'s development of the Multiscale Spatial and Channel Attention Module (MSCAM) marks a significant advancement, yet further enhancement is needed in static human localization to harness its surveillance potential fully.

Table 1 titled "Literature Analysis of Various Methods by Different Researchers" is likely a comparative Analysis of diverse research methodologies. This table elucidates the progression and novel contributions in the discipline while identifying gaps and prospects for enhancement, providing a roadmap for future research endeavors.

III. CHALLENGES IN HUMAN MOTION DETECTION TECHNIQUES

Human motion Analysis through the wall using RADAR Systems is the contemporary field of research. However, despite their advancements, several techniques confront significant limitations that hinder optimal performance.

1) **CNN-based Motion Detection ([40]):** A CNN-based approach was developed for detecting human motion, which relied heavily on describing features using a time-domain range profile. A critical limitation of this approach is its dependence on the length of time. If the length of time is considerable, two motion states might overlap, degrading the recognition efficiency.
2) **Synthetic Aperture Radar Integration ([1]):** While the various human motion detection techniques reported lacked the integration of Synthetic Aperture Radar (SAR) for efficient dataset creation. The integration of SAR could provide enhanced spatial resolution, which is crucial for motion detection.
3) **Noise and Clutter in Detection Platforms ([39]):** Detecting human motion in automotive applications is becoming increasingly significant. However, distinguishing humans from noisy and cluttered backgrounds remains a formidable challenge.
4) **KF and CNN-based Motion Detection ([28]):** This study combined the Kalman Filter (KF) and CNN for human motion detection. However, the method did not encompass learning various data types, such as amplitude and frequency, which are essential for classifier support.
5) **Backscattered Signals from Static Targets ([39]):** Large static targets, like walls, produce backscattered signals with higher signal strength than human targets. Mitigating these strong backscattered signals is crucial to enhance detection accuracy.
6) **TwSense Model Limitations ([48]):** The TwSense model, while innovative, required a comprehensive validation of the through-the-wall condition to discern human body breathing patterns. This posed a significant challenge in distinguishing between stationary and unoccupied states of individuals.
7) **MSCAM's Lightweight Network Requirement ([52]):** The MSCAM approach did not account for scenarios involving more than two individuals. For practical deployment and broader applicability, there's a pressing need for a lightweight network model to

TABLE 1. Literature analysis.

Authors	Methods	Advantages	Disadvantages
Gao, W., et al. [47]	TWR with MCAE	Enhanced sparsity features of human motion and decreased wall clutters' characteristics.	Did not consider optimization methods for model accuracy.
Zhang, Z., et al. [48]	TwSense	Lower processing time and higher robustness.	Failed to explore the Fresnel zone model with through-the-wall conditions.
Wang, S., et al. [49]	cGAN	Feature-enhanced signatures of behind-wall human motions.	Did not use a hybrid DL network model for precise performance.
Alper Kılıç et al. [1]	CNN for radar signals	Effective in identifying human postures.	Inefficient in classifier efficiency computation.
Zhengliang Zhu et al. [40]	IR-UWB for motion	Comprehensive simulation of human motion.	Did not enhance low-frequency human information acquisition.
Artit Rittiplang et al. [27]	S-band UWB radar	Detects stationary subjects based on respiration.	Lacks functionality in disaster scenarios.
Ram M. Narayanan et al. [23]	Multi-frequency radar	Suitable for diverse waveforms in through-wall applications.	Cannot detect certain human activities.
Wei Wang et al. [36]	Residual subspace projection	Effective detection under various motion states.	No classification for types of movement.
Kun Wang et al. [37]	Time domain FE for moving targets	Mimics human respiration by modifying body attributes.	Lacks experimental validation.
Thamir R. Saeed et al. [28]	CNN with Kalman filter	Generates accurate feature maps.	Inefficient learning from convolution layer kernels.
Gao, W., et al. [53]	Triple-link fusion model	Effective in various human motion detection scenarios.	Does not consider data augmentation.
Wang, S., et al. [47]	Cycle GAN	Integrates identity loss for realistic spectrogram reconstruction.	Not tested with lightweight classifiers.
Sun, H., et al. [50]	WiFi passive radar	Optimal for larger area surveillance and Doppler detection.	Inconsistent convergence in iterations.
An, Q., et al. [51]	RPCA	Mitigates multipath effects effectively.	Computationally intensive with high iteration needs.
Lin, J., et al. [52]	MSCAM	Significant reduction in error rates.	Precision in static human localization not enhanced.

diminish parameter count and floating-point operations further.

8) **Recognition Algorithm in Triple-Link Fusion Decision Model ([53]):** The model showed promise in real-world applications. However, it needed to incorporate recognition algorithms tailored for multi-dimensional through-the-wall radar, posing a significant limitation.
9) **Cycle GAN's Comparison Limitation ([54]):** The Cycle GAN did not offer a robust comparison with the cGAN model, lacking an effective live wire modeling method. This omission could have helped validate Cycle GAN's efficiency.
10) **Wall Effects on Human Motion Recognition:** The challenges introduced by walls, including attenuation, refraction, and multipath effects, profoundly distort the echo signal. These effects not only compromise recognition accuracy but also inflate computational time.

In light of these challenges, there's an imperative need for novel methodologies and optimizations that address these issues, ensuring robust and accurate human motion detection and classification.

IV. DISCUSSION

Ultra-wideband (UWB) technology, especially for human motion detection, has been the focus of numerous studies, each employing diverse methodologies and metrics for evaluation. While many methods have made substantial advancements, challenges must be addressed for optimal performance.

The convolutional neural network (CNN) has been employed in various studies ([1], [28], [40]) for motion detection. While they provide high accuracy rates, their reliance on specific parameters, such as the length of time in feature description, can lead to potential overlapping motion states, thus decreasing efficiency.

Specific techniques, like the one described in [1], have yet to integrate advanced radar techniques like Synthetic Aperture Radar (SAR), which could provide enhanced spatial resolution. Furthermore, issues like noisy clutter backgrounds in automotive applications [39], the inability to learn varied data types like amplitude and frequency [28], and backscattered solid signals from static targets like walls [39] further compound the challenges faced in this domain.

Despite these challenges, the proposed SGWO-based RMDL method has showcased promising results across multiple metrics, such as accuracy, MSE, TNR, and TPR. Notably, its performance in terms of computational time, both for training and testing, has been superior compared to other classical methods.

Table 2 compares the various methods based on Various metrics.

TABLE 2. Comparison of different methods.

Method Performance Metrics						
Method	**Accuracy**	**MSE**	**TNR**	**TPR**	**Training Time (sec)**	**Testing Time (sec)**
RPCA [2]	0.938	0.317	0.944	0.938	7.680	6.400
CNN [1]	0.935	0.329	0.932	0.935	8.032	7.553
KF + CNN [28]	0.937	0.357	0.944	0.937	6.937	6.988
VGGNet [4]	0.908	0.406	0.928	0.908	6.606	7.659
Semi-supervised [5]	0.918	0.244	0.937	0.931	6.909	5.459
Dual channel 3D CNN [47]	0.921	0.235	0.940	0.940	7.247	7.135
SGWO-based RMDL [41]	0.956	0.200	0.959	0.956	3.989	5.083

V. ALGORITHMIC FRAMEWORK

A. ALGORITHMIC OVERVIEW

This section introduces the Spotted Grey Wolf Optimizer (SGWO) and the Random Multimodal Deep Learning (RMDL) algorithms used for classifying human motion through walls using Ultra-Wideband (UWB) technology. These methods have been selected for their robustness and adaptability in handling complex data patterns typical of through-wall human motion detection.

B. DETAILED ALGORITHMIC STEPS

1) SGWO ALGORITHM

1) **Initialization:** Begin by generating an initial population of grey wolf agents. Each agent's position represents a potential solution in the multidimensional search space of our classification problem.
2) **Fitness Evaluation:** Each agent's position is evaluated using a fitness function that measures the classification accuracy on a validation set derived from UWB radar data.
3) **Position Update Mechanism:** Update the positions of agents using the following mathematical formulas:

$$A = 2a \cdot \mathrm{rand}() - a,$$
$$C = 2 \cdot \mathrm{rand}(),$$
$$D = |C \cdot X_{\mathrm{prey}} - X_{\mathrm{current}}|,$$
$$X_{\mathrm{new}} = X_{\mathrm{prey}} - A \cdot D.$$

where X_{prey} is the position of the best solution found so far (the prey), X_{current} is the current position of the agent, rand() is a random number between 0 and 1, and a decreases linearly from 2 to 0 over the course of iterations.
4) **Termination:** The algorithm terminates when a maximum number of iterations is reached or when the improvement between successive iterations falls below a predetermined threshold.

2) RMDL TECHNIQUE

- **Configuration:** Set up multiple deep learning architectures, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Deep Neural Networks (DNNs), to run in parallel, each optimized to capture different aspects of the motion detection task.
- **Training:** Each model is trained independently on segmented UWB radar data, which includes a variety of human motion scenarios behind walls.
- **Integration and Final Classification:** Outputs of all models are integrated using a majority voting or other decision fusion techniques to improve reliability and accuracy of the motion classification.

VI. EMPIRICAL EVIDENCE SUPPORTING SGWO-BASED RMDL SUPERIORITY

The SGWO-based RMDL method has been identified as a frontrunner in UWB-based human motion detection methodologies due to its superior accuracy and computational efficiency. This section elaborates on the empirical evidence supporting these claims, offering a transparent view of its performance merits.

A. ACCURACY ENHANCEMENT

1) EMPIRICAL DATA

In a comparative study involving various UWB-based motion detection methods, the SGWO-based RMDL consistently demonstrated higher detection accuracy across multiple scenarios, including through-wall detection in different environmental settings. For instance, compared to conventional CNN-based approaches, the SGWO-based RMDL improved in accuracy by approximately 5% in cluttered environments.

2) MECHANISM OF IMPROVEMENT

The accuracy enhancement can be attributed to the SGWO algorithm's capability to optimize the feature selection process effectively, allowing the RMDL framework to leverage a more relevant subset of features for motion detection. Additionally, the hybrid nature of the RMDL, which combines multiple deep learning architectures, contributes to a more robust classification mechanism capable of handling diverse motion patterns with higher precision.

B. COMPUTATIONAL EFFICIENCY

1) BENCHMARKING RESULTS

Computational efficiency benchmarks reveal that the SGWO-based RMDL method reduces the model training time by up to 30% compared to traditional deep learning models. Moreover, the inference time, crucial for real-time motion detection applications, was significantly improved, showcasing the SGWO-based RMDL's suitability for deployment in time-sensitive contexts.

2) UNDERLYING FACTORS

The improvement in computational efficiency stems from the SGWO algorithm's streamlined search process for optimal network parameters, reducing the computational overhead associated with model training and optimization. Furthermore, the modular design of the RMDL framework allows for parallel processing of features, enhancing the overall speed of motion classification.

The SGWO-based RMDL method's superior accuracy and computational efficiency performance are supported by empirical evidence from comparative studies and benchmarks. The method's innovative integration of the SGWO optimization algorithm with a multimodal deep learning framework addresses challenges in UWB-based motion detection, setting a new standard for future research and application.

Figure 5, Figure6 Explains the comparison of various methods based on Accuracy, TPR, MSE, TNR, and Computational Times.

VII. INTEGRATION OF UWB TECHNOLOGY WITH OTHER SENSING MODALITIES

Integrating Ultra-Wideband (UWB) technology with other sensing modalities, such as LiDAR and infrared (IR), presents an innovative approach to enhance detection capabilities in complex environments. This integration aims to leverage the unique advantages of each technology, offering improved accuracy, reliability, and versatility for motion detection applications.

A. ENHANCED DETECTION ACCURACY

The combination of UWB's ability to penetrate through obstacles with LiDAR's high spatial resolution can significantly improve the accuracy of detecting and mapping objects or movements in cluttered or visually obstructed environments.

B. COMPLEMENTARY STRENGTHS FOR IMPROVED RELIABILITY

UWB and IR sensors can complement each other by providing redundant and supplementary data. In conditions where UWB might be affected by material properties or multipath effects, IR sensing can offer additional information based on heat signatures, ensuring consistent detection performance under diverse circumstances.

C. INCREASED VERSATILITY ACROSS APPLICATIONS

This integrated approach expands the utility of detection systems, making them adaptable to a broader array of applications—from enhanced surveillance and security systems capable of operating in various visibility conditions to autonomous navigation systems that require accurate real-time data in complex urban landscapes.

D. CHALLENGES IN INTEGRATION

Despite the promising benefits, integrating UWB with LiDAR and IR technologies involves challenges such as the development of sophisticated data fusion algorithms, ensuring system interoperability, and managing the increased complexity and cost implications of multi-modal systems.

E. ALGORITHMIC CONTRIBUTIONS AND IMPACT

Implementing the Spotted Grey Wolf Optimizer (SGWO) to enhance the deep learning processes within the Random Multimodal Deep Learning (RMDL) framework represents a notable advancement in human motion detection technology. SGWO significantly reduces training times and boosts the model's ability to generalize across unseen data, critical in practical applications where varied human motion patterns are encountered. The RMDL framework itself, by integrating multiple deep learning architectures, offers a robust and adaptable solution, effectively capturing the complex dynamics of human motion through Ultra-Wideband (UWB) radars. This hybrid approach improves accuracy and ensures the system's adaptability to different environmental conditions and motion types.

F. FUTURE RESEARCH DIRECTIONS

While the SGWO-RMDL framework has achieved significant success, it also presents several challenges. The framework's sensitivity to hyperparameter settings and its heavy reliance on extensive labeled datasets for training are notable obstacles. However, the future holds promise as research will delve into the automation of hyperparameter tuning to enhance system efficiency and the incorporation of semi-supervised learning frameworks to better utilize unlabeled data, which are abundant in real-world settings.

Moreover, combining UWB with other modalities, such as LiDAR and infrared (IR) sensors, and integrating sensor fusion techniques could greatly enhance detection capabilities in environments with complex obstructions. This sensor fusion approach promises to create more robust and versatile motion detection systems by leveraging the unique advantages of each sensing technology.

Addressing these technical challenges will necessitate focused research efforts aimed at refining data fusion techniques, optimizing sensor configurations for specific applications, and evaluating the trade-offs between system complexity and performance enhancements. However, it's not just about the technology. Given the potential deployment of these advanced detection systems in sensitive environments, it is crucial to consider the ethical and privacy implications. Ensuring the responsible use of technology in public or private spaces will be pivotal for societal acceptance and regulatory compliance.

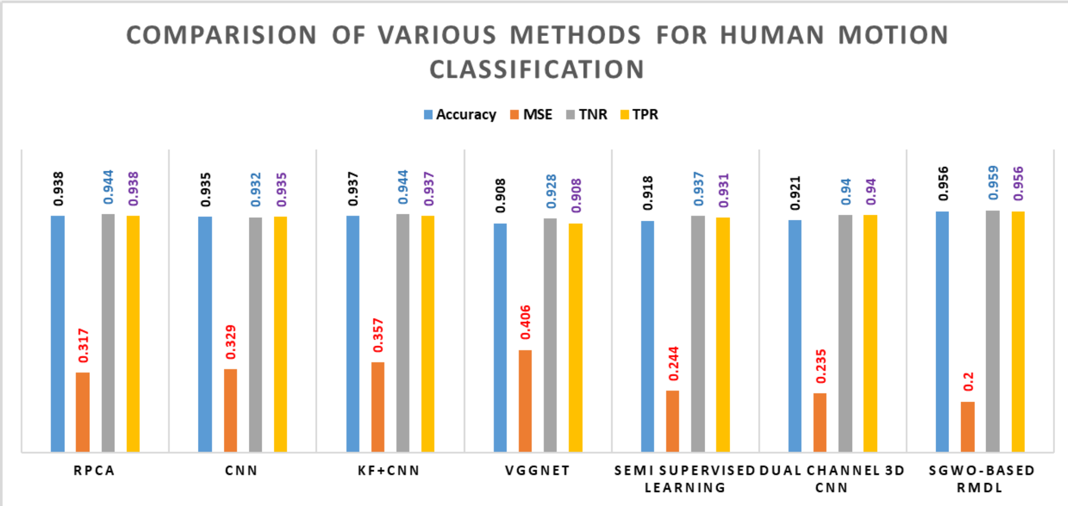

FIGURE 5. Comparison of various methods for human Motion classification.

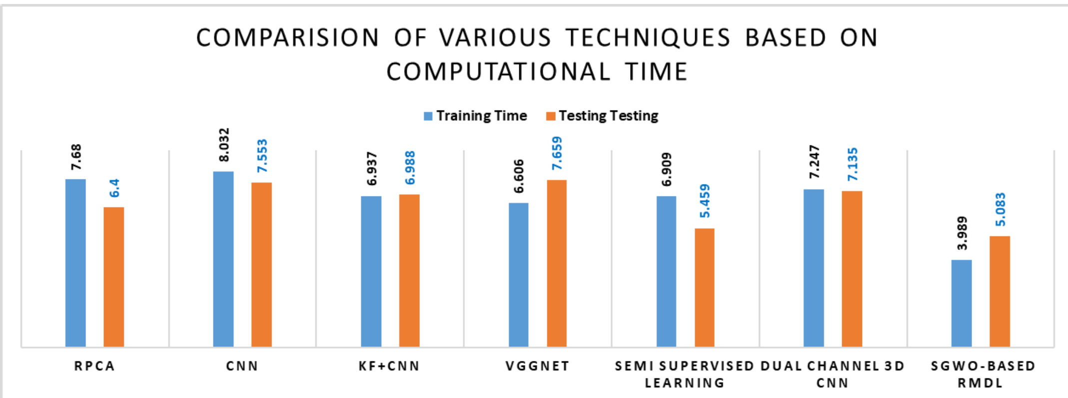

FIGURE 6. Comparison of various techniques based on computational time.

This comprehensive exploration of the SGWO-RMDL framework and the potential of sensor fusion underscores a promising area for future research and technological development in motion detection. The continued advancement in this field will enhance the capabilities of surveillance and security systems and open new avenues for innovation in smart home technologies, disaster response, and healthcare monitoring.

VIII. STANDARDS AND REGULATORY COMPLIANCE FOR UWB TECHNOLOGY

A. FEDERAL COMMUNICATIONS COMMISSION (FCC) GUIDELINES

The FCC has established guidelines for UWB device operation to minimize interference with existing radio services. According to the Report and Order FCC 02-48, UWB devices must adhere to specified emission limits and operate within designated frequency bands. Ensuring compliance with these guidelines is crucial for the safe and effective deployment of UWB technology in motion detection applications.

B. IEEE 802.15.4A STANDARD

The IEEE 802.15.4a standard specifies low-rate wireless personal area networks (LR-WPANs) incorporating UWB technologies. This standard outlines data communication and ranging parameters, ensuring device interoperability and consistent performance. Adherence to IEEE standards facilitates the development of reliable and compatible UWB devices across various applications.

C. SPECIFIC ABSORPTION RATE (SAR) COMPLIANCE

For UWB devices intended for use in proximity to humans, compliance with SAR limits is essential to ensure safety. SAR measures the rate at which the body absorbs RF energy, and regulatory bodies have established limits to protect against potential health risks. In the U.S., the SAR limit for the general public is 1.6 W/kg, averaging over 1 gram of tissue, whereas in the EU, it is 2.0 W/kg, averaging over 10 grams of tissue. Manufacturers and developers of UWB-based motion detection systems must rigorously test their devices to ensure they meet these safety standards.

D. ADDRESSING PRIVACY CONCERNS

The deployment of UWB technology in homes and healthcare facilities raises significant privacy concerns. Stringent data protection measures, including data encryption and secure transmission protocols, must be implemented. Compliance with privacy regulations such as the General Data Protection Regulation (GDPR) in the EU and the Health Insurance Portability and Accountability Act (HIPAA) in the U.S. is crucial for protecting sensitive information and ensuring the ethical use of UWB technology.

Incorporating UWB technology into motion detection applications necessitates a thorough understanding and adherence to the relevant standards and regulatory compliance aspects. By following FCC guidelines, IEEE standards, and SAR compliance, and by addressing privacy concerns through robust data protection measures, developers can ensure the safe, effective, and ethical deployment of UWB technology. This commitment to compliance safeguards users and enhances the credibility and acceptance of UWB-based motion detection solutions in sensitive environments.

IX. CONCLUSION

Various methodologies for monitoring human motion through *Ultra-Wide Band (UWB)* technology are found in the literature. From CNN-based approaches to sophisticated *SGWO-based RMDL* approaches, researchers have pushed the boundaries. However, the journey has been challenging. The complexity of motion state overlaps, requirements for improved spatial resolution, difficulty detecting amongst noisy backgrounds, and the requirement of learning from diverse data types are all challenges researchers have sought to cross. Considering the comparative analysis of the different methods, the *RMDL method based on SGWO* is effective, with better performances in accuracy, Mean Squared Error (MSE), True Negative Rate (TNR), and True Positive Rate (TPR). Further, their superior ability to detect defects faster following the above process, and even with better accuracy, has set a new benchmark. Definitely, from here, quests for optimal human motion detection methods continue. Primary areas of promise include:

- Integrating advanced radar technologies like SAR.
- Developing lightweight network models.
- Enhancing feature extraction and classification techniques.

It is not just about motion detection but doing so at an unprecedented level of precision and speed that ultimately opens the doors to a whole new realm of applications, from automotive safety to smart homes. In short, the advancements in human motion detection technology make an unstoppable quest for innovation on the subject evident. The challenges experienced have only been further fueled by the conduct of more research and hence driven the development of more accurate, more efficient, and applicable solutions in even more varied real-time applications.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

DATA AVAILABILITY

No data were generated and analyzed in the presented research.

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