UWB Radar Features for Distinguishing Humans From Animals in an Actual Post-Disaster Trapped Scenario

LI ZHAO1, MA YANGYANG2, ZHANG YANG1, LIANG FULAI1, YU XIAO1, QI FUGUI1, LV HAO1, LU GUOHUA1, AND WANG JIANQI1

1Department of Medical Electronics, School of Biomedical Engineering, Fourth Military Medical University, Xi’an 710032, China
2Air Force Hospital of Southern Theater Command of PLA, Guangzhou 510062, China

Corresponding authors: Lu Guohua (lugh1976@fmmu.edu.cn) and Wang Jianqi (wangjq@fmmu.edu.cn)

This work was supported in part by the Key Research and Development Plan of Shaanxi Province under Grant 2020SF-384, in part by the Key Industry Innovation Chain of Shaanxi Province under Grant 2021ZDLGY09-07, and in part by the National Natural Science Foundation of China under Grant 31600796.

This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by the Laboratory Animal Welfare and Ethics Committee of Fourth Military Medical University under Approval No. IACUC-20201201, Dated December 1, 2021, and performed in line with the Declaration of Helsinki.

ABSTRACT
Distinguishing humans from animals using ultra-wideband (UWB) radar is necessary in post-disaster emergency rescues to prioritize and thereby optimize the distribution of labor and material resources. However, current studies are few and have only been implemented in simple laboratory environments, such that the effectiveness of these approaches cannot be guaranteed in rescue situations. This study describes experiments under actual post-disaster emergency rescue scenarios, for which the signal-to-noise ratio of UWB radar is seriously degraded owing to multipath effects and a complicated ruin environment. Four distinguishing features are extracted from aspects of wavelet entropy, correlation coefficient, and energy to classify humans from animals. Analysis of feature effectiveness showed that each feature could identify humans from animals individually. The largest difference between humans and animals was found in a feature which combines advantages of the correlation coefficient and energy simultaneously. There was no overlap between the human and animal values for this feature among the 20 sets of radar data collected. This is the first attempt to distinguish humans from animals in an actual post-disaster trapped condition, and it yielded four features of strong classification ability. We envision this study to advance real-world applicability of UWB radar in post-disaster emergency rescue.

INDEX TERMS
Correlation coefficient, distinguishing between human and animal, multipath effect, post-disaster rescue, ultra-wideband (UWB) radar.

I. INTRODUCTION

Ultra-wideband (UWB) radar has gained increasing research interest for its potential in many civilian and military applications, mainly because of its advantages penetrating obstacles [1]–[4]. UWB radar can provide high-precision localization in through-obstacle situations and possesses excellent time resolution. Thus, applications such as gesture recognition [5], medical monitoring [6], target imaging [7], and target tracking [8] using UWB radar have been possible and show considerable market potential. In particular, UWB radar has become the most reliable technological method in many post-disaster emergency rescue applications, such as post-earthquake and mine disaster rescue missions [9].

A research priority for post-disaster emergency rescue situations is the capability to distinguish humans from animals. Such capability can provide rescue priority the order and optimize the distribution of human and material resources. Nevertheless, recent studies have focused on distinguishing between free-space situations and the moving status of targets. Wang et al. [10] proposed a feature of respiration and
heartbeat energy ratio to distinguish humans from dogs for free-space vital sign monitoring. A combined Gaussian mixture and hidden Markov model has also been used to identify slow-moving humans from animals to detect potential poachers in nature reserves [11]. However, these types of studies are not suitable for post-disaster emergency rescue applications because survivors are often trapped under obstacles of building ruins where they cannot move freely. Through-obstacle penetration and target stationary status are thus fundamental features in post-disaster rescue scenarios.

The authors’ team have designed methods for distinguishing stationary humans from animals under specific through-obstacle conditions. Wang et al. [12] extracted features of improved wavelet entropy and its standard deviation for the differentiation of stationary humans from dogs through a 28-cm thick brick wall. Subsequently, a support vector machine method that extracted 12 different features was proposed under similar experimental conditions to improve the accuracy and robustness of differentiation [13]. Recently, Ma et al. [14] designed a multiscale residual attention network under the same experimental conditions as that of [13] with an aim to expand the animal species that can be distinguished, including common city pets such as dogs, cats, and rabbits. However, the experimental scenarios in [12]–[14] are very simple. There is only a single straight brick wall between the targets and the UWB radar. In actual post-disaster emergency rescues, the targets are usually trapped and buried under the obstacles of building ruins. Here, static multipath effects [15]–[16] are significant and need to be accounted for. Such effects are caused by mutual interaction between the targets and the surrounding environment on the path of radar electromagnetic waves from transmission to reception [17]. Thus, the effective power of signal (Ps) is attenuated and the power of noise (Pn) is amplified because of the extended transmitting path and the increased reflection times of radar waves. Thereby, the signal-to-noise ratio (SNR), which is calculated by SNR = 10lg(Ps/Pn), is significantly degraded [18]. As the robustness and reliability of the proposed methods in a simple laboratory environment cannot be guaranteed, it is thus necessary to implement studies under more complex and realistic experimental scenarios.

To enhance the practicability of methods for distinguishing between stationary humans and animals, the experimental scenarios of this study were under triangle-shaped ruins which mimic the actual post-disaster trapped conditions of survivors. Subsequently, some novel and effective classification features are proposed from aspects of correlation coefficient, energy, and wavelet entropy. Finally, the experimental results verify the effectiveness of the pro-posed features. To the best of our knowledge, this is the first study to perform experiments under an actual post-disaster trapped scenario through which a novel and effective method for distinguishing stationary humans from animals is proposed. The study enhances the potential and promotes the application of UWB radar technology in post-disaster emergency rescue.

II. UWB RADAR SYSTEM

A block diagram of the UWB radar system is shown in Figure 1. The microcontroller controls the oscillator to generate trigger pulses with a 500 MHz centre frequency and 128 kHz pulse repetition frequency. Most of the trigger pulses are sent to excite the transmitter antenna (TA) to transmit the radar electromagnetic waves. Meanwhile, the remaining trigger pulses are used to turn on the delay unit to produce a series of software-controlled range gates of 300 ps width. Subsequently, the echoes of the radar waves that carry the target information are received by the receiving antenna (RA). However, only the echo parts within the width of the range gates can be amplified and integrated by the amplifier and integrator, respectively. Finally, the processed radar waves are returned to the microcontroller through a high-speed analog-to-digital converter (ADC). The most relevant key parameters of the UWB radar system setup are listed in Table 1.

![FIGURE 1. Block diagram of the ultra-wideband (UWB) radar system. TA, transmitter antenna; RA, receiving antenna; ADC, Analog-to-Digital Converter.](image)

| TABLE 1. Key parameters of the UWB radar system. |
|-----------------------------------------------|
| Parameters          | Values           |
| Centre Frequency   | 500 MHz          |
| Bandwidth          | 500 MHz          |
| Rang Points         | 2048             |
| Detection Range    | 0-3 m            |
| Sampling Speed      | 64 Hz            |

The detection range of the UWB radar system was controlled by software. The range was set to a total of 2048 range points corresponding to a 3 m distance, giving a sub-motion detection resolution of 3 m/2048≈1.5 mm, which is precise enough to detect the motion on the target chest caused by respiration. A 64 Hz sampling speed implies that there are 64 waveforms per second during the observation time (also known as slow time in radar technology). Based on this setup, the radar data form is described as D(m, n), m = 1, 2, …, M, n = 1, 2, …, N, M = 2048, N = 64 × T, where T represents the total slow time.

III. FEATURE EXTRACTION

In actual post-disaster emergency rescues, survivors are usually buried under building ruins. SNR of the radar data can be
seriously degraded by the static multipath that is caused by the mutual interactions between the targets and the surrounding ruins. As such, previous methods used in a laboratory environment with only a single brick wall between the target and the UWB radar can lose real-world effectiveness. Here, with an environment mimicking an actual post-disaster rescue site, we found certain features extracted from aspects of correlation coefficient, wavelet entropy, and energy to be the most effective and robust in distinguishing human from animal.

A. SIGNAL PRE-PROCESSING
Prior to feature extraction, the collected radar signal requires pre-processing to eliminate as much noise as possible. The steps for the pre-processing procedure are illustrated in Figure 2.

For the first step shown in Figure 2, the collected radar data \( D(m, n) \) are processed by range accumulation, which aims to compress the \( M = 2048 \) range points to 200 range points. This step improves computational efficiency and still guarantees the validity of the data information. The step is implemented by:

\[
D_{\text{ra}}(x, n) = \frac{1}{10} \sum_{m = 10(x-1)+1}^{10x} D(m, n). \tag{1}
\]

where \( x = 1, 2, \ldots, X, X = 200 \).

Subsequently, normalization along the slow time is implemented to make the signal energy of humans and animals comparable, defined as:

\[
D_{n}(x, n) = \frac{D_{\text{ra}}(x, n) - \min(D_{\text{ra}}(x, n))}{\max(D_{\text{ra}}(x, n)) - \min(D_{\text{ra}}(x, n))} - 1. \tag{2}
\]

Direct current removal is then performed to eliminate baseline drift caused by the structure of the radar system, described as:

\[
D_{\text{dc}}(x, n) = D_{n}(x, n) - \frac{1}{100} \sum_{n}^{n+99} D_{n}(x, n). \tag{3}
\]

Following direct current removal, low-pass filtering with a 2-Hz cut-off frequency is performed to eliminate the high-frequency noise, defined by:

\[
D_{\text{lp}}(x, n) = D_{\text{dc}}(x, n) * h(t), \tag{4}
\]

where \( h(t) \) denotes the impulse function of the finite impulse response filter [21].

Lastly, adaptive filtering based on the least mean square algorithm is utilized to eliminate respiration-like clutter and suppress strong interference as in [22], to give the completed pre-processed radar data denoted as \( D_{\text{af}}(x, n) \).

B. FEATURES EXTRACTED FROM THE ASPECT OF CORRELATION COEFFICIENT
The correlation coefficient of the signal at the target position and signals at other range points can vary differently between humans and animals [13], [23]. Thus, two correlation coefficient-corresponding features were extracted.

1) SUM OF CORRELATION COEFFICIENT WITHIN A FIXED RANGE WINDOW (SCC)
Calculation of the SCC is determined as:

\[
\text{SCC} = \frac{\sum_{x = t_p - w}^{t_p + w} \text{Cov}(D_{\text{af}}(t_p, n), D_{\text{af}}(x, n))}{\sqrt{\text{Var}(D_{\text{af}}(t_p, n), D_{\text{af}}(x, n))}}, \tag{5}
\]

where \( \text{Cov} \) denotes the operation of covariance, \( \text{Var} \) denotes the operation of variance, \( t_p \) denotes the range points at the actual target position, and \( w \) denotes the half width of the fixed range window. It should be noted that the range points of the target position are in the middle of the fixed range window.

2) CHANGE RATE OF CORRELATION COEFFICIENT WITHIN A FIXED RANGE WINDOW (CRCC)
In experimental scenarios of actual post-disaster emergency rescues, it was found that the correlation coefficient within a fixed range window for humans changed slowly (with the difference between the maximum and the minimum being small), whereas for dogs it changed rapidly (with the difference between the maximum and the minimum being larger). The CRCC is designed to reflect these differences between humans and dogs, and is determined as:

\[
\text{CRCC} = \frac{\max \text{Corr}(X_{tp}) - \min \text{Corr}(X_{tp})}{\max \text{Corr}(X_{tp})}, \quad \text{s.t.} t_p - w \leq X_{tp} \leq t_p + w, \tag{6}
\]

where \( \text{Corr} \) represents the correlation coefficient of the signal at the target position and signals at other range points within the fixed-range window, and “s.t.” is a mathematical symbol and means “subject to.”

C. FEATURES EXTRACTED FROM THE ASPECT OF ENERGY COMBINING CORRELATION COEFFICIENT
The correlation coefficient as used here is a parameter that describes the degree of synchronous trend between two signals. The larger the correlation coefficient of the two signals, the closer they are to each other. In the UWB radar data, if the correlation coefficient of the signal in the target position \( (S_{tp}) \) and one other signal \( (S_{op}) \) is large enough, then \( S_{op} \) can be considered as the mapping of \( S_{tp} \) to the other range points.
This association is caused by the environmental multipath effect or the thickness of the target’s body.

In the experiment, we found that the five largest correlation coefficients between $S_{op}$ and $S_{sp}$ were large enough to be statistically relevant for humans, where the smallest value among them was usually larger than 0.6. Thus, we can consider them as valid interfering target signals. However, for animals, there are usually only three correlation coefficients that are larger than 0.6. The fourth and fifth largest correlation coefficients were usually smaller than 0.6. Consequently, the last two $S_{op}$ among the five signals can be considered as noise or clutter. After signal pre-processing, the energy of the noise or clutter was very low. Based on this knowledge and experience, we designed the feature of the sum of energy from noise or clutter. This association is caused by the environmental multipath effect or the thickness of the target’s body.

The procedure for calculating the MMWE is as follows:

(a) Find the target position by choosing the range point with the maximum energy:

$$tp = \max_x \sum_n \text{Daf}(x,n)^2. \quad (7)$$

(b) Calculate the correlation coefficient between $S_{op}$ and $S_{sp}$, and denote it as $\text{Corr}(x)$. $op$ denotes all the signal positions within the radar detection range other than the target position. Namely, $op$ is a positive integer, and $op \in [1, tp - 1] \cup [tp + 1, T]$. $X$.

(c) Find the largest five values in $\text{Corr}(x)$ and denote the range points corresponding to the five largest values as Mrp [5].

(d) Normalize the five signals for $\text{Daf}(\text{Mrp},n)$ to $[0, 1]$ along the direction of the range points according to:

$$\text{Daf}(\text{Mrp},n) = \frac{\text{Daf}(\text{Mrp},n) - \min(\text{Daf}(\text{Mrp},n))}{\max(\text{Daf}(\text{Mrp},n)) - \min(\text{Daf}(\text{Mrp},n))} - 1. \quad (8)$$

(e) Calculate SECC by:

$$\text{SECC} = \left[ \sum \text{Daf}(\text{Mrp},n) \right]^2. \quad (9)$$

**D. FEATURES EXTRACTED FROM ASPECTS OF WAVELET ENTROPY**

In actual post-disaster emergency rescue scenarios, we found that the SNR of the human signal was better than that of the dog signal on average. Thus, the mean wavelet entropy within a fixed range window of the signal (MMWE) was extracted to describe these differences.

Wavelet entropy is a parameter used to quantitatively measure the functional dynamics of order/disorder in microstates based on the orthogonal discrete wavelet transform [12], [24].

The procedure for calculating the MMWE is as follows:

(a) Generate a set of elementary functions of the wavelet family $\psi_{j,n}(t)$ by dilations and translations of a unique mother wavelet:

$$\psi_{j,n}(t) = 2^{0.5j} \psi(2^j t - n), \quad (10)$$

where $j = -1, -2, \cdots, -J, J = \log_2 N$ is the number of resolution levels, and $n$ is the number of points along the slow time in the radar data.

(b) Implement the discrete wavelet transform of the radar signal $S(t)$:

$$C_j(n) = \int S(t) \psi_{j,k}(t) dt, \quad (11)$$

where $C_j(n)$ is the local residual error between successive signal approximations at resolutions $j$ and $j-1$.

(c) Calculate the relative wavelet energy $Rwe(j)$ at each resolution $j$:

$$Rwe(j) = \frac{\sum_n |C_j(n)|^2}{\sum_j \sum_n |C_j(n)|^2}. \quad (12)$$

(d) Calculate the wavelet entropy:

$$WE = - \sum_j Rwe(j) \times \ln(Rwe(j)). \quad (13)$$

(e) Divide the radar signal $S(t)$ into 128 non-overlapping frames of equal length along the direction of slow time, and then calculate the mean wavelet entropy for each signal at different range points $MWE_x$ by:

$$MWE_x = \frac{1}{\lceil N/128 \rceil} \sum_{f=1}^{\lceil N/128 \rceil} WE_x(f). \quad (14)$$

(f) Calculate the MMWE:

$$\text{MMWE} = \frac{1}{2w + 1} \sum_{x=tp-w}^{tp+w} MWE_x, \quad (15)$$

where $w$ denotes the half width of the fixed range window.

**IV. EXPERIMENTAL RESULTS**

**A. EXPERIMENTAL SCENARIOS**

To mimic actual post-disaster emergency rescue scenarios, we used the training site for post-disaster rescue of the Fire and Rescue Department of Shandong Province in China. Two identical experimental scenarios for the test subjects are shown in Figure 3. In Figure 3(a), a male target lies inside the ruins in a triangular cavity. The human target is surrounded by ruins in the illumination direction of the UWB radar where the multipath effect is significant. The ruins were built using reinforced concrete (RC), with the maximum width being 53 cm.

In Figure 3(b), a female beagle dog replaced the human male. The dog was supplied by the Experimental Animal Centre of the Fourth Military Medical University. The dog was three years old and weighed approximately 16 kg. To keep the dog stationary during the experimental process,
the dog was anesthetized with isoflurane using a gas anae-
thesia machine. Isoflurane anaesthesia has little influence on
respiration and heartbeat in anesthetized targets [19], [20].
The beagle dog regained consciousness and recovered to
move freely within three to five minutes of testing. The dog
experiment was subjected to IACUC-20201201.

B. RESULTS OF SIGNAL PREPROCESSING

An original radar signal that is typically collected is shown in
Figure 4 below.

For the human target, the signal was clear after pre-
processing, as illustrated in Figure 5(a). The target position
can be readily identified at approximately 1 m distance
and observed to have a clean respiration signal with obvi-
ous periodicity. However, there are many other mapping
signals present with that at the target position. For exam-
ple, the mapping signals at approximately 2.3 m are very
significant.

In contrast, the preprocessed radar signal for the dog can
be significantly less clean and the periodicity of respiration
is relatively poor, as shown in Figure 5(b). The target position
can be found by Equation (7) at approximately 1 m, but there
is still a lot of clutter and mapping signals caused by the
environmental multipath effect.

Comparing these typical results, it is clear that the quality
of the preprocessed radar signals for dogs is degraded more
seriously than that for humans. This can hinder the ex-
traction of clean respiration signals, but it can be an advantage in
distinguishing humans from dogs. The features extracted in
this study are based on the differences in these preprocessed
radar signals.
C. FEATURE COMPARISON BETWEEN HUMANS AND ANIMALS

1) COMPARISON OF SCC AND CRCC
To compare SCC and CRCC, the half width of the fixed-range window was empirically chosen as $w = 3$. Comparison of the trend of the correlation coefficient in the fixed range window for a human target and a dog target is shown graphically in Figure 6.

The average of the correlation coefficient for the human target is evidently larger than that of the dog target, with the features of SCC reflecting this difference. Moreover, we found that the minimum of the correlation coefficient of the dog target was usually smaller than 0 within the fixed range window, whereas that of the human target was usually larger than 0. The maximum correlation coefficients for both humans and dogs were always 1. Thus, the CRCC within the fixed range window of a human target is usually larger than that of a dog target, with the features of the CRCC reflecting this difference.

2) COMPARISON OF SECC
To compare SECC for the human and dog target, we collected 10 sets of original radar data for each. The time interval to collect each set of data was more than five minutes, and the total slow time of each set after preprocessing was 30 s. Comparative results for the SECC values of the human and dog target are shown in Figure 7 as boxplots.

The average value of SECC for the human target, which is shown by the red line in Figure 7, is obviously higher than that for the dog target. In addition, the minimum SECC for a human target was larger than the maximum SECC for a dog target. Independent sample T-test was performed to test whether there is a significant difference between the SECC values of human and dog targets. Two-tailed distribution was chosen and the result was $P \approx 1.4 \times 10^{-6} \ll 0.01$. These results indicate that there are large differences in the SECC values between humans and dogs.

3) COMPARISON OF MMWE
For comparison of MMWE in the human and dog targets, the half width of the fixed range window was also empirically chosen as $w = 3$ (the same as that when calculating SCC and CRCC). The trend of $MWE_x$ between the human and dog targets is illustrated in Figure 8.

As can be seen in Figure 8, the average of MWEx for the human target is evidently larger than that of the dog target. Correspondingly, the MMWE of the human target is larger than that of the dog target.

D. ANALYSIS OF FEATURE EFFECTIVENESS
To assess the effectiveness of the proposed features in a single radar acquisition, the comparative values between the human and dog targets among the 10 sets of radar data are shown in Figure 9. The blue triangle represents the values of the human target, and the green hexagon represents the values of the dog target. For some radar acquisitions in the set, the values of some features overlap, either because of differences in the surrounding environment influencing data collection or from variability in the radar system at the time of collection.

In Figure 9, it can be seen that the features of SCC, CECC, and MMWE cannot identify a human target from a dog target solely on the basis of a single radar acquisition. However, the feature values of SECC exhibit a large difference between humans and dog targets with no overlap in values. Consequently, it is suggested that SECC can serve as the primary feature when distinguishing between humans and animals under actual post-disaster scenarios, while the other
three features of SCC, CECC, and MMWE can serve as secondary or auxiliary features.

V. DISCUSSION
To the best of our knowledge, this is the first study to distinguish humans from animals in actual post-disaster scenarios rather than simple laboratory environments. Four UWB radar features were designed to accomplish this goal. Analysis of feature effectiveness showed that the proposed features can accomplish the classification sufficiently well when used separately from each other. In particular, the feature values of SECC showed significant differences between human and dog targets. However, further improvements could be made to improve the method’s systematic accuracy and the applicability of UWB radar in actual scenarios. For example, multiple target scenarios where human and animal are at one place simultaneously should be added. In addition, the target numbers and the signal acquisition times should be increased as much as possible. Thereby, some novel and effective classification methods such as machine learning and deep learning can be utilized.

VI. CONCLUSION
This study distinguished between humans and animals under actual post-disaster emergency rescue scenarios, where the SNR of the UWB radar data collected is seriously degraded because of significant multipath interference from reinforced concrete walls. To distinguish humans from dogs in this type of scenario, four features of SCC, CRCC, SECC, and MMWE were designed and extracted from the aspects of the correlation coefficient, wavelet entropy, and energy. In particular, the design of the four features utilized the advantage of the SNR difference between human and animal targets. Analysis of feature effectiveness showed that all four features can accomplish the mission of distinguishing human from animal well when used alone. In particular, there are significant differences in SECC values between the human and dog targets, demonstrating that the combination of the correlation coefficient and energy has the best classification performance.

This is the first attempt to distinguish humans and animals in realistic post-disaster rescue scenarios. We envision that the proposed method can improve the applicability of UWB radar in post-disaster emergency rescue to further enhance its real-world potential.

ACKNOWLEDGMENT
The authors would like to thank the Fire and Rescue Department of Shandong Province in China for providing the experimental site. (Zhao Li and Yangyang Ma are co-first authors.)

REFERENCES
[1] Y. Zhang, F. Qi, H. Lv, F. Liang, and J. Wang, “Bioradar technology: Recent research and advancements,” IEEE Microw. Mag., vol. 20, no. 8, pp. 58–73, Aug. 2019.
[2] C. Li and J. Lin, Microwave Noncontact Motion Sensing and Analysis. Hoboken, NJ, USA: Wiley, 2013.
[3] J. Li, Z. Zeng, J. Sun, and F. Liu, “Through-wall detection of human being’s movement by UWB radar,” IEEE Geosci. Remote Sens. Lett., vol. 9, no. 6, pp. 1079–1083, Jun. 2012.
[4] J. D. Taylor, Ultra Wideband Radar Technology. New York, NY, USA: CRC Press, 2001.
[5] F. Qi, H. Lv, J. Wang, and A. E. Fathy, “Quantitative evaluation of channel micro-Doppler capacity for MIMO UWB radar human activity signals based on time–frequency signatures,” IEEE Trans. Geosci. Remote Sens., vol. 58, no. 9, pp. 6138–6151, Sep. 2020.
[6] H. Hong, L. Zhang, H. Zhao, H. Chu, C. Gu, M. Brown, X. Zhu, and C. Li, “Microwave sensing and sleep: Noncontact sleep-monitoring technology with microwave biomedical radar,” IEEE Microw. Mag., vol. 20, no. 8, pp. 18–29, Aug. 2019.
[7] G. Smith, F. Ahmad, and M. G. Amin, “Micro-Doppler processing for ultra-wideband radar data,” Proc. SPIE, vol. 8361, May 2012, Art. no. 83610L.
[8] J. Yan, J. Dai, W. Pu, H. Liu, and M. Greco, “Target capacity based resource optimization for multiple target tracking in radar network,” IEEE Trans. Signal Process., vol. 69, pp. 2410–2421, 2021.
[9] H. Burchett, “Advances in through wall radar for search, rescue and security applications,” in Proc. IET Conf. Crime Secur., Jun. 2006, pp. 511–525.
[10] P. Wang, Y. Zhang, Y. Ma, F. Liang, Q. An, H. Xue, and Y. Yu, H. Lv, and J. Wang, “Method for distinguishing humans and animals in vital signs monitoring using IR-UWB radar,” Int. J. Environ. Res. Public Health, vol. 16, no. 22, p. 4462, Nov. 2019.
[11] W. D. van Eeden, J. P. de Villiers, R. J. Berndt, W. A. J. Nel, and E. Blasch, “Micro-Doppler radar classification of humans and animals in an operational environment,” Expert Syst. Appl., vol. 102, pp. 1–11, Jul. 2018.
[12] Y. Wang, X. Yu, Y. Zhang, H. Lv, T. Jiao, G. Lu, W. Li, Z. Li, X. Jing, and J. Wang, “Using wavelet entropy to distinguish between humans and dogs detected by UWB radar,” Proc. Electromagn. Res., vol. 139, pp. 355–352, 2013.
[13] Y. Ma, F. Liang, P. Wang, H. Lv, X. Yu, Y. Zhang, and J. Wang, “An accurate method to distinguish between stationary human and dog targets under through-wall condition using UWB radar,” *Remote Sens.*, vol. 11, no. 21, p. 2571, Nov. 2019.

[14] Y. Ma, F. Qi, P. Wang, F. Liang, H. Lv, X. Yu, Z. Li, H. Xue, J. Wang, and Y. Zhang, “Multiscale residual attention network for distinguishing stationary humans and common animals under through-wall condition using ultra-wideband radar,” *IEEE Access*, vol. 8, pp. 121572–121583, 2020.

[15] G. Gennarelli and F. Soldovieri, “Multipath ghosts in radar imaging: Physical insight and mitigation strategies,” *IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens.*, vol. 8, no. 3, pp. 1078–1086, Mar. 2015.

[16] R. Zetik, M. Eschrich, S. Jovanoska, and R. S. Thoma, “Looking behind a corner using multipath-exploiting UWB radar,” *IEEE Trans. Aerosp. Electron. Syst.*, vol. 51, no. 3, pp. 1916–1926, Jul. 2015.

[17] G. Gennarelli, G. Vivone, P. Braca, F. Soldovieri, and M. G. Amin, “Comparative analysis of two approaches for multipath ghost suppression in radar imaging,” *IEEE Geosci. Remote Sens. Lett.*, vol. 13, no. 9, pp. 1226–1230, Sep. 2016.

[18] R. C. Qiu, “A generalized time domain multipath channel and its application in ultra-wideband (UWB) wireless optimal receiver design—Part II: Physics-based system analysis,” *IEEE Trans. Wireless Commun.*, vol. 3, no. 6, pp. 2312–2324, Nov. 2004.

[19] P. Maud, O. Thavarak, L. Cédrick, B. Michèle, B. Vincent, P. Olivier, and B. Régis, “Evidence for the use of isoflurane as a replacement for chloral hydrate anesthesia in experimental stroke: An ethical issue,” *BioMed Res. Int.*, vol. 2014, pp. 1–7, Feb. 2014.

[20] X.-Y. Wu, Y.-T. Hu, L. Guo, J. Lu, Q.-B. Zhu, E. Yu, J.-L. Wu, L.-G. Shi, M.-L. Huang, and A.-M. Bao, “Effect of pentobarbital and isoflurane on acute stress response in rat,” *Physiol. Behav.*, vol. 145, pp. 118–121, Jun. 2015.

[21] A. Chandra and S. Chattopadhyay, “A novel approach for coefficient quantization of low-pass finite impulse response filter using differential evolution algorithm,” *Signal, Image Video Process.*, vol. 8, no. 7, pp. 1307–1321, 2012.

[22] Z. Li, W. Li, H. Lv, Y. Zhang, X. Jing, and J. Wang, “A novel method for respiration-like clutter cancellation in life detection by dual-frequency IR-UWB radar,” *IEEE Trans. Microw. Theory Techn.*, vol. 61, no. 5, pp. 2086–2092, May 2013.

[23] Y. Ma, P. Wang, W. Huang, F. Qi, F. Liang, H. Lv, X. Yu, J. Wang, and Y. Zhang, “A robust multi-feature based method for distinguishing between humans and pets to ensure signal source in vital signs monitoring using UWB radar,” *EURASIP J. Adv. Signal Process.*, vol. 2021, no. 1, pp. 1–24, Dec. 2021.

[24] O. A. Rosso, S. Blanco, J. Yordanova, V. Kolev, A. Figliola, M. Schürmann, and E. Başar, “Wavelet entropy: A new tool for analysis of short duration brain electrical signals,” *J. Neurosci. Methods*, vol. 105, no. 1, pp. 65–75, Jan. 2001.