Performance Analysis of Denim-Based Body-Worn UWB Antenna for Classification of Human Activities

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Abstract The application-centric approach of classification techniques implemented for recognition of human movements and activities is sought after in present scenario. Recognizing and classifying human movements and activities enables the utility and development of diverse applications, comprising continuous health and fitness status observation, real-time posture detection, assisted living, robotics, context-enabled gaming, etc. The major emphasis of this work is to demonstrate the suitability of compact ultra-wideband antenna as a wearable device for classifying fifteen human body activities. This research paper presents the performance analysis of flexible textile substrate-based compact wearable antenna. Machine learning algorithms are implemented on observed body activities datasets observed from on body antennas for classification.

Keywords WBAN · UWB · Denim-based antenna · Classification techniques · Machine learning

1 Introduction

Now-a-days, flexible wearable smart devices based wireless technologies are in high demand to enhance interactive communication among human and healthcare devices and systems. Wireless Body Area Network (WBAN) is applied to develop optimized

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design antenna sensors for biomedical utility and to study their electromagnetic characteristics [1]. A small-sized flexible ultra-wideband (UWB) antenna with slotted patch and swastika-shaped geometry is presented in [2]. As stated in [3], electromagnetic properties of On-body antenna wave propagation and radiation have been well explored for diverse applications including WBAN. The classification of various body movements is studied like sitting idle, walking stairs, climbing, etc., using the motion artifacts observed in ECG signals. It is demonstrated that different separations between body movements have been applied to determine the accuracy of classification [4].

A feasibility study in [5] states that miniature wireless transceivers are implied on human body to classify different human body limb movements such as arm and leg motion. The healthcare system is undergoing rapid transformation in which continuous tracking of human movements is feasible. Lightweight, high-performance wearable sensors are used to detect abnormal conditions by monitoring physiological parameters so that timely utmost care can be provided. Researchers in [6] reviewed the existing systems on wearable sensor-based activity monitoring of humans and addressed related issues to be addressed to cope up with the challenges faced by current system. Zaric et al. in [7] proposed a novel design of miniature low-profile UWB antenna for WBAN usage.

The classification of human body movements based on spectrograms of S_{21} and S_{11} of body-worn antennas with deep convolutional neural networks (DCNNs) is proposed in [8, 9]. The Dynamic Time Warping algorithm (DTW) has been implemented for the classification based on reflection coefficient of designed circularly polarized antenna The Eu (Euclidean distance) of test signal with respect to reference signal is analyzed for all activities considered for classification [10].

Multilayer Perceptron (MLP) is a neural network that applies backpropagation as supervised learning method and connects various layers to a directed graph. Every node except the nodes present at the input, all other nodes has a nonlinear trigger function. K-Nearest Neighbor (KNN) is a supervised algorithm in which the labeled data has to be provided to classifier model to classify the points based on the distance between those points to the nearest points. Support Vector Machines (SVMs) can be used for linear classification as well as for nonlinear classification. Random Forest (RF) Algorithm analyzes the degree of separation to provide ensemble to aggregate over such that each tree will divide depending on various characteristics. The classification is performed by every tree. Then Forest choses the classification with majority of votes. Bootstrap aggregating is blend of aggregation and bootstrapping that diminishes variance [11]. Long Short-Term Memory network can be made to learn the electroencephalogram datasets for the classification of different limb movements [12]. A dynamic time-warping (DTW) algorithm is explored to recognize six daily activities on the basis of variation in impedance [13]. The possibility of classification of hand gestures has been explored using variation in input impedance of monopole antennas. The spectrograms of various hand and finger gesture images were classified using DCNN [14].

The majority of earlier related research works are sensor-based activities' recognition system which possess limitation in terms of hardware, power constraints, and safety issues associated with on body applications. Therefore, to fill this gap, there is a need to explore and implement small-sized body-worn UWB antenna-based reliable activities monitoring system without using other sensors. In the presented work, the key contributions are:

1. Design and performance analysis of Denim-based wearable ultra-wideband (ranging from 3.1 to 10.6 GHz) antennas.
2. Performance exploration of designed UWB antenna for classification of human activities in context to accuracy and compare it with related sensor-based systems mentioned in the literature to affirm its suitability and supremacy for the classification of human activities.

Table 1 summarizes comparable body movement recognition and classification techniques mentioned in literature. The literature review regarding human activities classification systems and related work UWB antenna design is described in Sect. 1. The antenna-based experimental set-up is illustrated in Sect. 2. The classification results are highlighted in Sect. 3. Section 4 concludes the presented work.

Table 1 Summary of body movement recognition and classification mentioned in literature

Ref. No.	Sensor or device used	Classification basis	Application
[10]	On-body miniaturized antennas	Eu distance	Human activity classification system
[11]	Compact dual-band antenna	S_{11} and S_{21}	Limb movement classification system
[12]	Electroencephalogram (EEG)	EEG movement datasets	Limb movement classification system
[13]	Monopole antenna	Variation in impedance	Human activity classification system
[14]	Two monopole antennas	Optical images of impedance variation	Hand movement recognition
Proposed	Denim-based UWB antenna	S_{11} and S_{21}	Recognize human body activities (body positions, arm movements, wrist, and finger gestures)

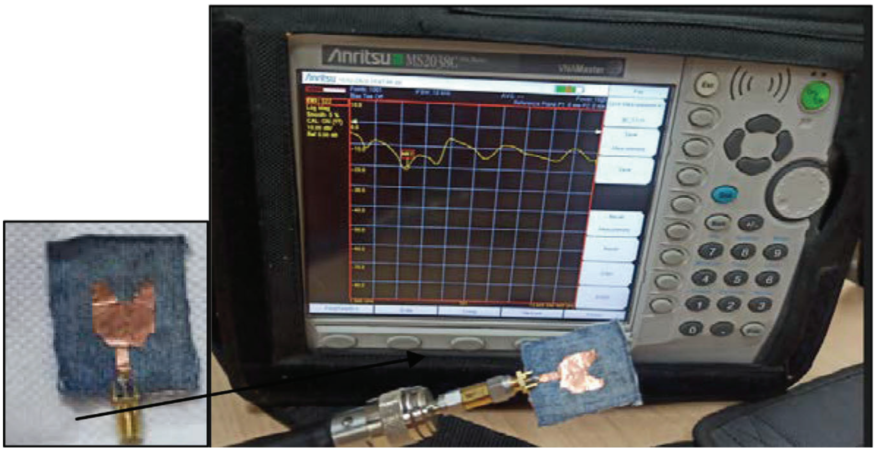


Fig. 1 Design geometry of implemented antenna [15]

2 Antenna-Based Experimental Setup

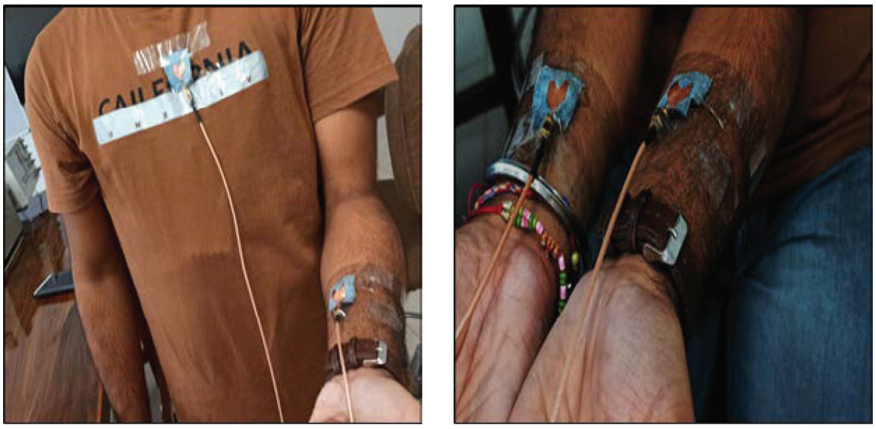
2.1 Antenna Design

The present works focuses on implementation of body-worn textile antenna design [15] in which denim material is used as substrate. Denim material exhibits low loss tangent tan $\delta = 0.025$ and low relative permittivity $\varepsilon r = 1.7$ that results in higher bandwidth and reduced surface wave losses. The implemented antenna design is presented in Fig. 1. The partial ground structure with slots in antenna leads to superior antenna performance characteristics [16].

2.2 Proposed Methodology for Dataset Creation

In presented work, Denim substrate based on body transmitting and receiving antenna sets is deployed on human body. Five healthy human subjects: three males and two females with an average age of 25 years were participated in the process of dataset creation by performing 15 different body activities with ten repetitions. Two locations are considered for antenna placements as illustrated in Fig. 2. In first scenario, one antenna was placed at chest and on wrist. In second scenario, the antennas were deployed on left and right wrist.

The S_{11} and S_{21} (reflection coefficient and transmission coefficient, respectively) were monitored using antennas through Anritsu MS2038C Vector Network Analyzer. Two resonant frequencies, i.e., 3.83 and 9.8 GHz shown in Ref. [16] are considered for denim-based antenna in UWB (3.1–10.6 GHz) range. For each observed antenna,



(a) (b)

Fig. 2 Illustration of antenna placement on subject **a** Scenario 1, **b** Scenario 2

Table 2 Human activities considered

Class	Activity
Arm activities	Boxing, rowing, clapping
Wrist gestures	Hands open, hand close, wrist flexion, wrist extension
Body postures	Sitting, standing, hands bend, body bend
Finger movements	Wave in, wave out, click, swipe

performance characteristics like S_{11} and $S_{21,}$ 3000 datasets (5 subjects × 15 human activities × 2 frequencies × 10 repetitions × 2 location of antenna placement) were created using Denim substrate-based antenna. Following human body activities are considered for recognition and classification as shown in Table 2.

3 Classification Results and Discussion

3.1 Classification Techniques Implemented

Random Forest (RF), Support Vector Machines (SVMs), Extreme Gradient Boosting (XGB), K-Nearest Neighbors (KNNs) algorithm, and Multilayer Perceptron (MLP) classification algorithms are implemented on observed scattering parameters datasets for various activities mentioned in Table 2.

Table 3 Classification results

Classification algorithm	Classification accuracy
Random Forest (RF)	98.20
Support Vector Machines (SVMs)	98.70
Extreme Gradient Boosting (XGB)	99.25
K-Nearest Neighbors (KNNs)	94.06
Multilayer Perceptron (MLP)	89.9

3.2 Classification Results

Accuracy is the ratio of all correct outcomes to entire outcomes and is implied as a measure to analyze the performance of the model. Precision is how accurately a classification models made positive predictions. Recall is the measure of the effectiveness of a classifier in identifying all relevant outcomes from a dataset. To analyze overall performance of classification learning algorithm, $F1$-score is employed [17, 18]. In [19], new ensemble deep learning classifier with multiple levels that combines effect of diverse classifiers is applied for time-series-based pattern classification for recognizing simple and complex types of movements. The performance optimization of the conventional 3DCNN can be achieved by amalgamation of the Convolutional Long Short-Term Memory stages into it [20].

The comparative analysis of the classifiers can be made on the basis of performance metrics of classification algorithms mentioned in Table 3. The comparison of proposed classification results with related research work is presented in Table 4.

The possible applications as the outcome of the present research include recognition of four classes of human body activities, i.e., body positions, arm movements, wrist, and finger gestures. These applications result in human fitness observation, assisted living, context-enabled gaming, human machine interfacing, and gesture recognition systems for elderly, ill, or handicapped persons.

Table 4 Comparison of proposed classification results with comparable research work mentioned in reference

Ref. No.	Activities considered	Classification technique	Classification accuracy
[10]	Three arm activities	DTW	Not reported
[11]	Five hand activities	SVM, KNN, DT, GNB, SDG, MLP	S_{11}–49%, S_{21}–39% (SVM) S_{11}–50%, S_{21}–41% (KNN) S_{11}–72%, S_{21}–99% (DT) S_{11}–50%, S_{21}–40% (GNB) S_{11}–52%, S_{21}–63% (SDG) S_{11}–70%, S_{21}–99% (MLP)
[12]	Left and right-hand movements	LSTM	98.3%
[13]	Six human daily activities	DTW	98.9%
[14]	Ten hand and finger movements	Transfer learning	94.6% with Z_{11} and Z_{22}
Proposed	Fifteen body movements (3 hand activities, 4 wrist gestures, 4 body postures, and 4 finger movements)	RF, SVM, XGB, KNN, and MLP	98.20% (RF) 98.70% (SVM) 99.25% (XGB) 94.06% (KNN) 89.90% (MLP)

4 Conclusion

This research effort focuses on application of transmission and refection coefficients (S_{21} and S_{11}) of on body denim substrate-based UWB transmitting and receiving antennas set for classification of body movements. Main emphasis of this research work will be on efficient human body movement classification system for WBAN based on machine learning.

The present work also demonstrates the performance evaluation of the diverse classification techniques as mentioned in Table 4 for implementation for recognition of human body activities. The machine learning classifier algorithms are implemented on observed datasets of antenna parameters like scattering parameters (S_{11} and S_{21}) associated with different human activities for classification. The highest classification accuracy of 99.25% is observed when XGB classification algorithm is used for classification. The presented work can be expanded as future work by inclusion of more number of body movements with enlarged datasets.

References

1. Hamdi, A., Nahali, A., Harrabi, M., & Brahem, R. (2023). Optimized design and performance analysis of wearable antenna sensors for wireless body area network applications. *JIT, 7*(2), 155–175. https://doi.org/10.1080/24751839.2023.2179909
2. Tiwari, B., Gupta, S. H., & Balyan, V. (2020). Design and comparative analysis of compact flexible UWB antenna using different substrate materials for WBAN applications. *Applied Physics A, 126*, 858. https://doi.org/10.1007/s00339-020-04011-5
3. Hall, P. S., Hao, Y., Nechayev, V. I., Alomain, A., Constantinou, C. C., Parini, C., Kamarudin, M. R.,. Salim, T. Z., David, T. M., Heel, D. T., Dubrovka, R., Owadall A. S., Song, W., Serra, A., Nepa, P., GaI1o, M., & Bozzetti, M. (2007). Antennas and propagation for on-body communication systems. *IEEE Antennas Propagation Magazine*, *49*(3), 41–58
4. Pawar, T., Chaudhuri, S., & Duttagupta, S. P. (2007). Body movement activity recognition for ambulatory cardiac monitoring. *IEEE Transactions on Biomedical Engineering, 54*(5), 874–882.
5. Guraliuc, A. R., Barsocchi, P., Potorti, F., & Nepa, P. (2011). Limb movements classification using wearable wireless transceivers. *IEEE Transactions on Information Technology in Biomedicine, 5*(3), 474–480.
6. Mukhopadhyay, S. C. (2015). Wearable sensors for human activity monitoring: A review. *IEEE Sensors Journal, 15*(3), 1321–1330.
7. Zaric, A., Costa, J. R., & Fernandes, C. A. (2014). Design and ranging performance of a low-profile UWB antenna for WBAN localization applications. *IEEE Transactions on Antennas and Propagation, 62*(12), 6420–6427.
8. Kim, Y., & Li, Y. (2017). Human activity classification with transmission and reflection coefficients of on-body antennas through deep convolutional neural networks. *IEEE Transactions on Antennas and Propagation, 65*(5), 2764–2768.
9. Gupta, S. H., Sharma, A., Mohta, M., & Rajawat, A. (2020). Hand movement classification from measured scattering parameters using deep convolutional neural network. *Measurement, 151*, 107258.
10. Peshwe, P. D., Joshi, N. Y, & Kothari, A. G. (2022). Human activity classification using on-body miniaturized antennas. Wireless Personal Communications
11. Ashish, P. U., Sharma, R. V., & Gupta, S. H. (2022). Classification of limb movements using different predictive analysis algorithms. *International Journal of Systems Assurance Engineering and Management, 13*, 1385–1395. https://doi.org/10.1007/s13198-021-01484-2
12. Zhang, G., Davoodnia, V., Sepas-Moghaddam, A., Zhang, Y., & Etemad, A. (2020). Classification of hand movements from EEG using a deep attention-based LSTM network. *IEEE Sensors Journal, 20*(6), 3113–3122. https://doi.org/10.1109/JSEN.2019.2956998
13. Li, Y., & Kim, Y. (2017). Classification of human activities using variation in impedance of single on-body antenna. *IEEE AWP Letters, 16*, 541–544. https://doi.org/10.1109/LAWP.2016.2588400
14. Alnujaim, I., Alali, H., Khan, F., & Kim, Y. (2018). Hand gesture recognition using input impedance variation of two antennas with transfer learning. *IEEE Sensors Journal, 18*(10), 4129–4135. https://doi.org/10.1109/JSEN.2018.2820000
15. Tiwari, B., Gupta, S. H. & Balyan, V. (2021). Investigation on performance of wearable flexible on-body ultra wide band antenna based on denim for wireless health monitoring. *Journal of Electronic Materials 50*(12), 6897–6909.https://doi.org/10.1007/S11664-021-09222-x
16. Tiwari, B., Gupta, S. H., & Balyan, V. (2021). Design and analysis of wearable textile UWB antenna for WBAN communication systems. In *LNNS* (Vol. 203, pp. 141–150). Springer. https://doi.org/10.1007/978-981-16-0733-2_10
17. Shalaby, E., ElShennawy, N. & Sarhan A. (2022). Utilizing deep learning models in CSI-based human activity recognition. *Neural Computing and Applications 34*, 5993–6010. https://doi.org/10.1007/s00521-021-06787-w

18. Gupta, S. (2021). Deep learning based human activity recognition (HAR) using wearable sensor data. *International Journal of Information Management Data Insights, 1*(2), 100046. https://doi.org/10.1016/j.jjimei.2021.100046
19. Kumar, P., & Suresh, S. (2023). Deep-HAR: An ensemble deep learning model for recognizing the simple, complex, and heterogeneous human activities. *Multimedia Tools and Applications*. https://doi.org/10.1007/s11042-023-14492-0
20. Vrskova, R., Kamencay, P., Hudec, R., & Sykora, P. (2023). A new deep-learning method for human activity recognition. *Sensors, 23*(5), 2816. https://doi.org/10.3390/s23052816