A method of obstacle identification in ultra wideband wireless sensor networks

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Abstract: Obstacle identification is a difficult task, which is more challenged in foliage environment. In this paper, a method of target detection is proposed, which attempts to extract information from the data being transmitted around the wireless sensor network (WSN) to identify targets that might be within the local, foliage obscured scene. The selected bispectra algorithm is applied to extract the feature vector, as well as radial-basis function (RBF) neural network is used to realise the obstacle classification. According to the experiment results, this method is able to identify the existence and the different distances of the obstacles measured in outdoor foliage scene with a good recognition rate.

Keywords: target detection; obstacle identification; UWB; ultra wideband; WSN; wireless sensor network; selected bispectra; RBF; radial-basis function; foliage environment.

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1 Introduction

Detection and classification of targets that obscured by foliage is of interest to both civilian and military communities, but there are leaves, trunks and canopies in this environment hindering the channel path between the transceivers, which makes it hard to exploit the traditional methods to detect invading obstacles. In recent years, many location-based algorithms for detecting physical obstacles and communication holes in wireless sensor networks (WSNs) have been proposed (e.g., Watfa and Commuri, 2006; Liu and Feng, 2007; Fang et al., 2004). These algorithms are based on the sensor's awareness of its own location with high accuracy, so the obstacles can be detected using a coordinate system computing approach executed by each sensor node and its neighbours. But neither GPS nor other localisation mechanisms can provide sufficiently accurate sensor location. Consequently, the use of location free algorithms has become increasingly common in recent years (e.g., Reichenbach et al., 2006; Dong et al., 2009; Saukh et al., 2010). But the algorithms suffer high communication overhead, which is not suitable for the detection of the obstacle. Although there are already some methods that can accomplish obstacle detection in WSNs without the need for any location information or any

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knowledge of the distance among the sensor nodes (e.g., Chu and Ssu, 2012), they still depend on the topology of the WSNs. Its original purpose is committed to improving the performance of most WSNs applications, but not to identifying invading target itself.

From the view of radar, obstacle identification is done through observing the back scattering (BS) or forward scattering (FS) signals, and this procedure usually needs a radar system. Conventional radars are mostly based on the BS signals. There have been a lot of researches and applications about obstacle identification based on BS signals (e.g., Raj et al., 2010; Segura et al., 2012). Recently, the unique characters of the FS signal have drawn more and more attentions. Forward scatter radar (FSR) is an extreme bistatic radar configuration, in which a sensed target is between transmitter and receiver with a bistatic angle β_{BA} of $170^\circ - 180^\circ$ (e.g., Hu et al., 2012), i.e., close to the radar baseline. The FSR could be effectively used to detect stealth and other such targets by extracting Doppler shift from the received signal. There have been a lot of successful applications such as convoy targets identification (e.g., Hu et al., 2012) and automatic target recognition (e.g., Cherniakov et al., 2006). But the FSR always suffers from target's crossing baseline perpendicularly. And the stationary target detection will not work with FSR, because no Doppler shift will be produced with stationary target. Moreover, FSR is not fit for such heavy scattering and sheltered scene as in the foliage environment. Although there are some other kinds of detection or imaging techniques working on the stationary target, such as forward-looking radar (e.g., Liao and Dogaru, 2012), ground penetrating radar (GPR) (e.g., Jin et al., 2012), they still depend on a relative movement between the radar and the target, and are not applicable for the foliage environment.

UHF/VHF synthetic aperture radar (SAR) systems have the ability to penetrate foliage, and obtain the SAR signature of concealed targets in foliage. These radar systems, which are also known as foliage penetrating (FOPEN) SAR, are being investigated for detection of stationary and moving man-made targets in foliage. There have been literature concentrating on the modelling of the target in the foliage environment (e.g., Dehmollaian and Sarabandi, 2006), unattended ground sensors (UGS) applications (e.g., Gallone, 2011) and 3D reconstructions of targets hidden beneath foliage (e.g., Nannini et al., 2012). The UHF/VHF bands have good foliage penetration ability, but the size of the antenna is too large. Although the models have good approximation to the target and the environment, they are always very complex and vary with environment, especially the density and species of the vegetation. And in most studies, the radar is outside the forest while the target is inside, which is not applicable to the WSNs environment.

From the WSNs perspective, UWB-IR technology has a number of inherent properties that are well suited to WSNs applications. UWB systems have potentially low complexity and low cost, with noise-like signal properties. And it has better penetration ability to passive interference, with very good time domain resolution allowing for precise location and tracking. There has been a great deal of algorithms and applications using UWB to detect targets, such as security check (e.g., Ariza and Thoma, 2012), human activities classification (e.g., Bryan et al., 2012), concealed obstacles classification (e.g., Dong et al., 2011) and human-target detection and surrounding structure estimation (e.g., Zhang et al., 2013). There are also many UWB WSNs applications such as video surveillance (e.g., Huang et al., 2006) and infrastructure monitoring (e.g., Mehta and Zarki, 2004). Some attempts are made to realise the target detection under foliage environment in UWB radar sensor networks (RSNs) (e.g., Liang and Liang, 2010). Although the UWB has advantages in the sheltered environment, the current method still needs many specified equipment to fulfil the detection job.

Therefore, in general, the existing radar systems are not appropriate to be applied in the WSNs. First of all, based on the mechanics of the conventional radar system, extra sensors like moving target indicator sensors will be necessary. That will be a very heavy burden to both the data transmission and energy cost, which is even unrealisable in the WSNs. Secondly, most of the radar systems are based on the prerequisites of an open area or special and expensive equipment like vector network analyser (VNA), which will be a burden that WSNs seldom meet and afford.

WSNs are generally deployed in an outdoor environment, and thus the signals are always affected by the presence of obstacles within the sensing field. The existence and the location of the target in the real environment will block part of the electromagnetic (EM) waves travelling from the transmitting antenna toward the receiving antenna. This will affect the communication channel, and the corresponding changes will be reflected in the signal's characters. Therefore, some channel information is carried on the signal waveform itself. There have been some papers about nature resonance of the target illuminated by the transmit signals, and most of them are about the BS signals (e.g., Chen and Shuley, 2012). Though the scattering in the sheltered environment is very complex and it is hard to get analytic solutions, the intrinsic information can be reflected in the signal waveforms. And the obstacle related information can be extracted by adapting proper algorithm.

In this paper, we focus on the challenging obstacle identification in foliage environment. There are leaves, trunks and canopies in this environment hindering the channel path between the transceivers, so it is hard to exploit the traditional methods to detect invading obstacles. We adopt pattern recognition ways to deal with this difficulty, and an obstacle detection and recognition method based on UWB and selected bispectra with RBF neural network as a classifier in WSNs is proposed. Proved by experiment, we are able to classify different obstacle in foliage environment, including line-of-sight (LOS), non-line-of-sight (NLOS) and different positions of the same obstacle. As this method focuses on the signal waveform only and bases on the normal WSNs model, we can exploit the existing equipment in the UWB WSNs as obstacle sensors and there is no need for extra radar sensors. The experiment results show that this method has a very good and robust classification ability, which gives a fine application prospect.

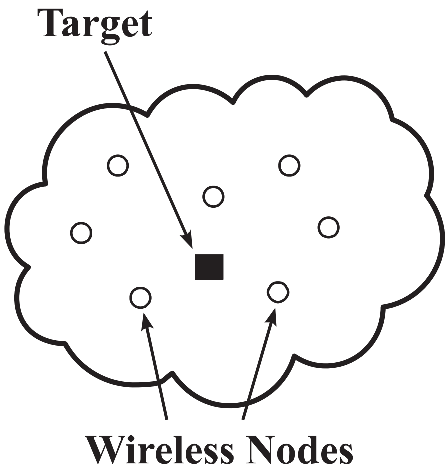
The paper is organised as follows. The methodology of the obstacle identification is discussed in Section 2. This is followed by introducing the selected bispectra algorithm with RBF neural network as classifier in Section 3. The experiment results of the method in identifying different obstacles data, which are measured in outdoor observed scene, are presented in Section 4 to demonstrate the effectiveness of this method. Finally, conclusions are made in Section 5.

2 Methodology of obstacle identification based on UWB and selected bispectra with RBF neural network as classifier

2.1 The basic idea

Our model is based on normal UWB WSNs, which is illustrated in Figure 1. The data used to identify the existence and the position of the obstacle are the received data at the receiver node, which is transmitted from another node in the WSNs. As this method focuses only on the received signal waveform, it is easy to obtain the data, which means there is no need for extra sensors. Then the identification of the obstacle and the normal node communication procedure are able to be performed simultaneously.

Figure 1 Normal UWB WSNs model in our method



When transmitted in the channel, the UWB signal is always been influenced by the obstacles. The sizes, materials of the obstacle will affect the radiation and scattering of electromagnetic waves, so there will be some changes in the amplitude and phase of the signal. But the scattering in the sheltered environment, such as the scene obscured by leaves, is very complex and the FS signals will interference with the incident signals. As a result, it is very hard to get analytic solutions. But the inherent reflection of the waveform of the existence and location of an object does exist. Especially when using the bispectra to analyse the signals, amplitude and phase information will be retained.

Then if the key different features among the received signals are extracted by discriminating against the information of different targets and their positions, there will be a possible way to identify the obstacles as well as their conditions. The means to discriminate the key features in this method is based on Selected Bispectra (e.g., Zhang et al., 2001), which is based on the Higher Order Spectral Analysis (e.g., Tsatsanis and Giannakis, 1992). The extracted features are some of the frequency points, which will be extremely important for the lack of capacity in WSNs. Moreover, we adapted the algorithm with estimation method to lower the complexity and be more practical to be applied in real implementation. This will be introduced in details in Section 2.2.

As the most distinguishing key features have been extracted, it is important to choose a proper classifier. The WSNs have a limit computing capacity for the sake of energy consumption and cost, so the classifier must be of excellent performance while the complexity is low. Here we choose the RBF neural network as the classifier. The parameters in the RBF neural network are very convenient for storage, which also enables this method to be applied in the normal WSNs. This will be discussed in details in Section 2.3.

By applying the techniques above, the identification can be done during the normal communications between the nodes in the WSNs, without any extra sensors. The whole algorithm of target identification will be shown in Section 2.4.

2.2 The feature extraction methods based on higher order spectral analysis

It is widely recognised (e.g., Tsatsanis and Giannakis, 1992) that the use of higher order statistics (cumulants and/or polyspectra) in feature extraction has the following advantages:

- cumulants/polyspectra retain both amplitude and phase information of a signal
- cumulants/polyspectra are translation (or shift) invariant
- cumulants/polyspectra have the immunity to additive Gaussian noise.

Although the bispectra have all the advantages of cumulants/polyspectra in feature extraction, there are serious limitations for bispectra application.

- the computation of bispectra in the whole triangular region is huge
- the two-dimensional (2D) template matching score in the classification is impractical.

We adopt the selected bispectra as the classification feature, in order to avoid the disadvantages, such as abandon the little contribution bispectra and a mass of cross-terms of the bispectra. Selected bispectra is first proposed by Zhang et al. (2001), and it is originally used for BS radar target recognition in the open air condition. Its basic idea is to select only the bispectra at individual bifrequency points with the most discriminant power as feature vectors. Therefore, it avoids the trivial and baneful bispectra or missing some important bispectra. The bispectra of a deterministic, continuous-time signal $x(t)$ is defined as

$$B(\omega_1,\omega_2)=\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty}c_{3x}(\tau_1,\tau_2)\mathrm{e}^{-j(\omega_1\tau_1+\omega_2\tau_2)}\mathrm{d}\tau_1\mathrm{d}\tau_2 \quad (1)$$

where

$$C_{3x}(\tau_1,\tau_2)=\int_{-\infty}^{+\infty}x^*(t)x(t+\tau_1)x(t+\tau_2)\mathrm{d}t \\ =E\left\{x^*(t)x(t+\tau_1)x(t+\tau_2)\right\} \quad (2)$$

is the triple correlation function of $x(t)$. For simplicity, denote $\omega=(\omega_1,\omega_2)$ and $B(\omega)=B(\omega_1,\omega_2)$. Suppose the training set consists of bispectra samples $\left\{B_k^{(i)}(\omega)\right\}_{k=1,2,\ldots,N_i}$ and $\left\{B_k^{(j)}(\omega)\right\}_{k=1,2,\ldots,N_j}$, where the subscript k stands for bispectra computed from the kth set of observed data, the superscript i represents the ith class of the signal, and N_i and N_j are the set numbers of observed data of the ith and jth class signals, respectively. In order to select the powerful bispectra set as the feature parameter set, the Fisher's class separability is chose as the discriminant measure function. Therefore, the Fisher class separability measure between the ith and jth classes is defined by

$$m^{(ij)}(\omega)=\frac{\sum_{l=i,j}[\mathrm{mean}_k(B_k^{(l)}(\omega))-\mathrm{mean}_l[\mathrm{mean}_k(B_k^{(l)}(\omega))]]^2}{\sum_{l=i,j}\mathrm{var}_k(B_k^{(l)}(\omega))} \\ i\neq j \quad (3)$$

where $\mathrm{mean}_k(B_k^{(l)}(\omega))$ is the mean (centroid) of all the sample bispectra at the frequency ω of the lth class; $\mathrm{var}_k(B_k^{(l)}(\omega))$ is the variance of all the sample bispectra at the frequency ω of the lth class; $\mathrm{mean}_l[\mathrm{mean}_k(B_k^{(l)}(\omega))]$ is the total centroid of all the sample bispectra at the frequency ω over all the classes. Here, we assume that $p(l)$ is the same for every class (i.e., equal probability).

The bispectrum of a discrete-time signal $x(n)$ can be calculated as

$$B(\omega)=X(\omega_1)X(\omega_2)X^*(\omega_1+\omega_2) \quad (4)$$

where $\omega=\omega_1,\omega_2$ and $X(\omega_i)$ is the local Fourier transform at a specific frequency point $\omega_i, i=1,2$. For the discrete-time signal of length T, we need to compute the Fourier transform $X(\omega_i),\omega_i\in\Omega$, where

$$\Omega=\left[\frac{q\pi}{2^d}:d=\lfloor\log_2 T-1\rfloor, 0\leq q<2^d, d,q\in Z\right] \quad (5)$$

where $\lfloor y\rfloor$ denotes the maximum integer not larger than y, and Z stands for the integer number domain.

In real implementation, the values of bispectrum can only be estimated based on the limited observation signals. The estimation can be divided into non-parameter estimation and parameter estimation (e.g., Li et al., 2011). A direct algorithm of non-parameter bispectrum estimation is adopted, which is based on Fast Fourier Transform, as follows.

- *Step 1*: Divide data $x(k)(k=1,2,\ldots,N)$ into K segments, each of which has M points, where $N=KM$, and then minus the average of each segment.
- *Step 2*: Calculate FFT of each segment.

$$\widehat{X}^{(i)}(\omega)=\frac{1}{M}\sum_{k=1}^{M}x^{(i)}(k)\exp\left(-\frac{j2\pi k\omega}{M}\right) \quad (6)$$

where $k=1,2,\ldots,M$ and $i=1,2,\ldots,K$.

- *Step 3*: Calculate

$$\widehat{B}_x^{(i)}(\omega_1,\omega_2)=M^2\widehat{X}^{(i)}(\omega_1)\widehat{X}^{(i)}(\omega_2)\widehat{X}^{(i)}(\omega_1+\omega_2) \quad (7)$$

- *Step 4*: The value of bispectrum estimation determined by the average of K segments.

$$\widehat{B}_x(\omega_1,\omega_2)=\frac{1}{K}\sum_{i=1}^{K}\widehat{B}_x^{(i)}(\omega_1,\omega_2) \quad (8)$$

After the bispectra of the kth observation record of the ith class signal $\widehat{B}_k^{(i)}(\omega)=\widehat{B}_k^{(i)}(\omega_1,\omega_2),\omega_1,\omega_2\in\Omega$ are computed for all i and k, we can calculate $m^{(ij)}(\omega)$ in equation (3).

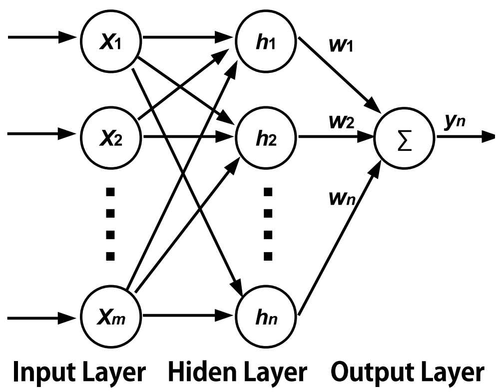
The larger $m^{(ij)}(\omega)$ is, the stronger the separability between class i and j. Therefore, we choose the feature frequencies set $\omega(h),h=1,\ldots,Q$ with Q largest separability measures among $m^{(ij)}(\omega)$ for all possible combinations (i,j), and call $\omega(h)=(\omega_{1,h},\omega_{2,h}),h=1,\ldots,Q$ the selected frequencies on the bifrequency plane $\omega_1-\omega_2$. So $B(\omega_{1,h},\omega_{2,h})$ are called the selected bispectra.

2.3 The classify method of the RBF neural network

The thought of RBF network is to take RBF as the 'basis' of the hidden layer units, so as to construct the hidden layer space (e.g., Ding et al., 2010). It is a nonlinear function that is symmetrical on the central points of the RBF are determined, then the input vector can be directly mapped to the hidden space. But the mapping from the hidden space to the output space is linear, that is, the linear weighting sum of the network unit output, the weight here is the networks adjustable parameters.

The RBF network is a three-layer feedforward network, which is composed by input layer, hidden layer and output layer, as shown in Figure 2. The hidden layer takes the RBF function as the activation function, generally we use Gaussian function.

Figure 2 Simplified structure of RBF neutral network



Suppose the network has m inputs and n outputs, the hidden layer has s neurons, the connection weight between the input layer and the hidden layer is w_{ij}, the threshold value of the hidden layer is b_j, the connection weight between the hidden layer and output layer is w_{jk}, the input of the hidden layer's jth neurons is:

$$r_j = \sqrt{\sum_i (w_{ij} - x_i)} \times b_j \tag{9}$$

where $i = 1, 2, \ldots, m, j = 1, 2, \ldots, s$.

The output of the jth neuron in hidden layer is:

$$h_j = \exp(-(r_j)^2) = \exp(-(\|w_{ij} - x_i\| \times b_j)^2) \tag{10}$$

The inputs of the output layer are the weighting sum of the neuron's outputs of each hidden layer, the activation function is a pure linear function, and the output is:

$$y_k = \sum_{j=1}^{s} h_j \times w_{jk} \tag{11}$$

where $j = 1, 2, \ldots, s, k = 1, 2, \ldots, n$.

3 The identification algorithm

Given original received samples $d_k^{(l)}(1), \ldots, d_k^{(l)}(M)$ of the kth observation record of the lth class of signal, where $l = 1, \ldots, c$ and $k = 1, \ldots, M_l$. The Training Algorithm is as below:

- *Step 1*: Use gate method to select N samples $x_k^{(l)}(1), \ldots, x_k^{(l)}(N)$ from the raw sample sequences which maintains the signal-majored part of the received samples, while the noise-majored part is ignored.
- *Step 2*: Estimate bispectra $\widehat{B}_k^{(i)}(\omega) = \widehat{B}_k^{(i)}(\omega_1, \omega_2), \quad \omega_1, \omega_2 \in \Omega$ with direct algorithm of non-parameter bispectrum estimation.
- *Step 3*: Use equation (3) to compute the Fisher class separability measure $m^{(ij)}(\omega)$ for all class combinations $(i,\ j)$, and requeue M largest measures such that

  $$m^{(ij)}(v_1) \geq m^{(ij)}(v_2) \geq \cdots \geq m^{(ij)}(v_M) \tag{12}$$

- *Step 4*: Calculate the normalised Fisher class separability measure

  $$\overline{m}^{(ij)}(v_p) = \frac{m^{(ij)}(v_p)}{\sqrt{\sum_{k=1}^{M} \left[m^{(ij)}(v_k)\right]^2}}, p = 1, \ldots, M \tag{13}$$

  Determine the 'effective' number of selected bispectra for between-class $(i,\ j)$, and denote it by $H^{(ij)}$. The corresponding frequencies $\left\{\omega^{(ij)}(p), p = 1, \ldots, H^{(ij)}\right\}$ are called the "effective" frequencies, and the repeated frequency for different combinations $(i,\ j)$ remains only one.
- *Step 5:* Arrange the obtained effective frequencies $\left\{\omega^{(ij)}(p), p = 1, \ldots, H^{(ij)}\right\}$ into the sequent $\left\{\omega^{(ij)}(q), q = 1, 2, \ldots, Q\right\}, Q = \sum_{(i,j)} H^{(ij)}$. And arrange the corresponding selected bispectra of the kth record in class l into the sequent $\left\{B_k{}^{(ij)}(q), q = 1, 2, \ldots, Q\right\}, Q = \sum_{(i,j)} H^{(ij)}$, $k = 1, \ldots, N_l$. The template feature vectors are given by $s_j = [B_k^{(l)}(1), \ldots, B_k^{(l)}(Q)]^T$ and the feature vector of the lth class is $S_l = \{s_i\}_{i=lN+1, lN+2, \ldots, (l+1)N}, l = 1, \ldots, c$.
- *Step 6*: Use the selected (powerful) bispectra to train the RBF neural network as classifier. Let $H = [h_{ij}]_{(c \times N) \times (c \times N)}$ represent the hidden node output matrix, where

  $$h_{ij} = \exp\left(-\frac{\|\overrightarrow{s_i} - \overrightarrow{s_j}\|^2}{\sigma^2}\right) \tag{14}$$

  and the variance σ^2 of the Gaussian kernel function is the total variance of all feature vectors $s_i, i = 1, \ldots, cN$. Hence, the weight matrix of the RBF neural network is given by

  $$\overrightarrow{W} = (\overrightarrow{H}^H \overrightarrow{H})^{-1} \overrightarrow{H}^H \overrightarrow{Y} \tag{15}$$

  where $\overrightarrow{Y}$ is the $(cN) \times c$ desired output matrix given by

  $$\overrightarrow{Y} = \begin{bmatrix} 1 \cdots 1 & 0 \cdots 0 & \ldots & 0 \cdots 0 \\ 0 \cdots 0 & 1 \cdots 1 & \ldots & 0 \cdots 0 \\ \vdots \ddots \vdots & \vdots \ddots \vdots & \cdots & \vdots \ddots \vdots \\ \underbrace{0 \cdots 0}_{N} & \underbrace{0 \cdots 0}_{N} & \cdots & \underbrace{1 \cdots 1}_{N} \end{bmatrix}^T \tag{16}$$

  Once the RBF neural network as classifier is trained, the weight matrix $\overrightarrow{W}$ is stored.
- *Step 7*: Let $\overrightarrow{x} = [s(1), s(2), \ldots, s(N)]^T$ is a feature vector computed from a set of measured data of an unknown target. Then, the RBF neural networks hidden node output vector $\overrightarrow{h} = [h_i]_{(cN) \times 1}$ corresponding to $\vec{x}$ can be computed as

  $$h_i = \exp\left(-\frac{\|\overrightarrow{x} - \overrightarrow{s_i}\|}{\sigma_i^2}\right) \tag{17}$$

  where the variance σ_i^2 is the variance of the feature vector $\overrightarrow{s_i}$ determined in the training phase. Then, the output vector of the RBF neural network is given by

  $$\overrightarrow{y} = \overrightarrow{W}^T h \tag{18}$$

  The class with the most frequency in $\overrightarrow{y}$ is considered the class of the unknown target.

Figure 3 The picture of the measure scene (see online version for colours)

4 Experiments and analysis

The measurement is set in the scene of a grove beside a main road. The measurement data are taken using PulsON 400 ranging and communications module (RCM) by the Time Domain Co., Ltd. The P400 RCM operating band is from 3.1 GHz to 5.3 GHz, with 4.2 GHz as the center frequency. Time Domain Broadspec dipole antennas are used for transmitting and receiving antennas, while the gain of the antenna is about 3dbi. The P400 RCM is able to transmit and receive user-defined data packet, and it is a low power consumption module, which enables it to be operated with battery supply. Hence, we use a pair of P400 RCM to demonstrate the validity of our method, which is a simulation of the real UWB WSNs environment. When applied to large WSNs with many nodes, there is a possibility to take advantage of the many pairs of the transceivers to improve the accuracy of the identification.

Two experiments, which are labelled Experiments A and B, are conducted in foliage environment in May and July, when the leaves of the trees are dense. The UWB-IR transmitter (TX) and UWB-IR receiver (RX) are separately placed at fixed positions with a same height of 1.5m from the ground. In the two measurements, the distances between TX and RX are 10.658 m and 19.136 m, respectively. The obstacle is set to be a human being, with a height and weight of 1.75 m and 68 kg. The picture of the measure scene is shown in Figure 3. The deployment of the measurement equipment and the topology of target position are illustrated in Figure 4.

Detailed parameters of Experiments A and B are shown in Tables 1 and 2. Both experiment are used for two types of identification. The first one is to identify whether the channel is LOS or NLOS, i.e., the existence of the obstacle. The second one is designed to identify the position of the target, i.e., the different distances between the receiver and the obstacle, which is also shown in Figure 3.

Table 1 Parameters of Experiment A

Experiment A class	*Sample records*	*Obstacle to Rx distance: L*	*LOS\ NLOS*
A1	600	(No obstacle)	LOS
A2	600	3.90 m	NLOS
A3	600	6.40 m	NLOS
A4	600	6.82 m	NLOS

Table 2 Parameters of Experiment B

Experiment B class	*Sample records*	*Obstacle to Rx distance: L*	*LOS\ NLOS*
B1	600	(No obstacle)	LOS
B2	600	3.88m	NLOS
B3	600	6.69 m	NLOS
B4	600	9.15 m	NLOS
B5	600	11.92 m	NLOS

The sample records for each class are 600, and 350 sampled points in each record. Examples of the sample records with and without human in the foliage environment are shown in Figure 5. We adopt the gate method to maintain 70 points from the 5 points before the peak to 65 points after the peak. Then the main energy of the signal will be saved, while the noise majored part is ignored. When identifying LOS and NLOS, 300 LOS and 300 NLOS data are randomly selected for training, while 300 LOS and 300 NLOS data, other than the chosen data for training, are used for testing. The training NLOS data are consist of all the NLOS groups, for instance in Experiment A, the 300 training NLOS data are consist of 100 data from each of A2, A3 and A4. We select different numbers of extracted features to verify the validity of our methods. The corresponding results are shown in Figures 6 and 7. More detailed results are shown in Tables 3–6.

Figure 4 The topology of the measured scene

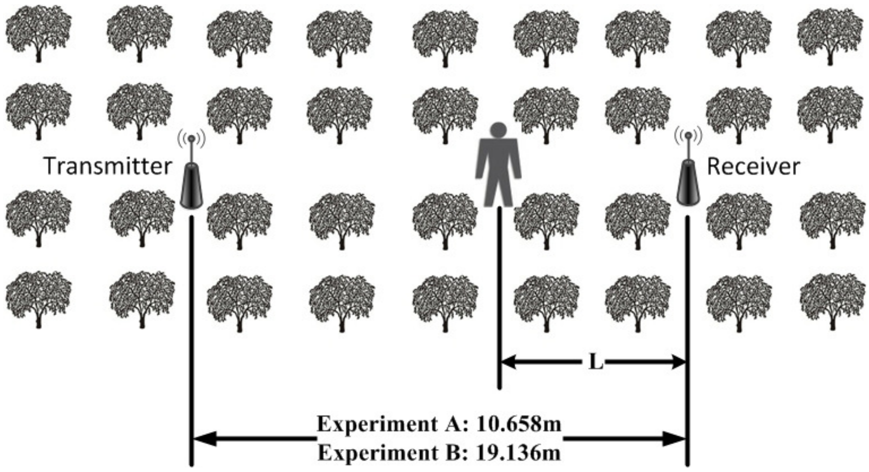


Figure 5 Examples of the sample records with and without human in the foliage environment

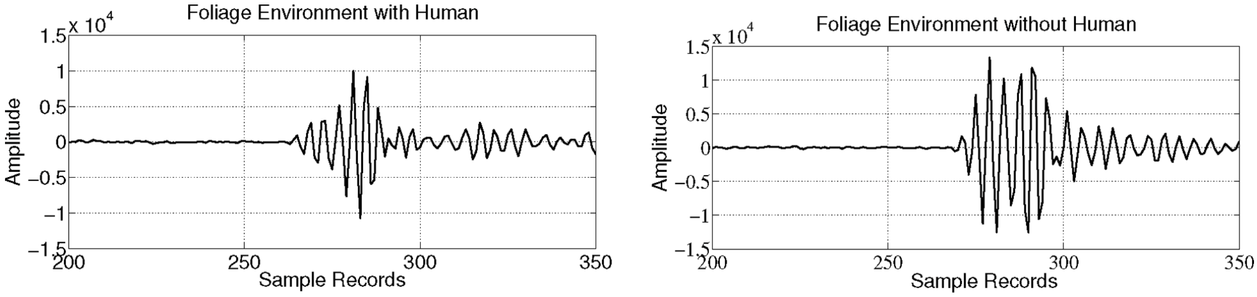


Figure 6 Average recognition rate vs. number of features, when applying the method to identify LOS and NLOS

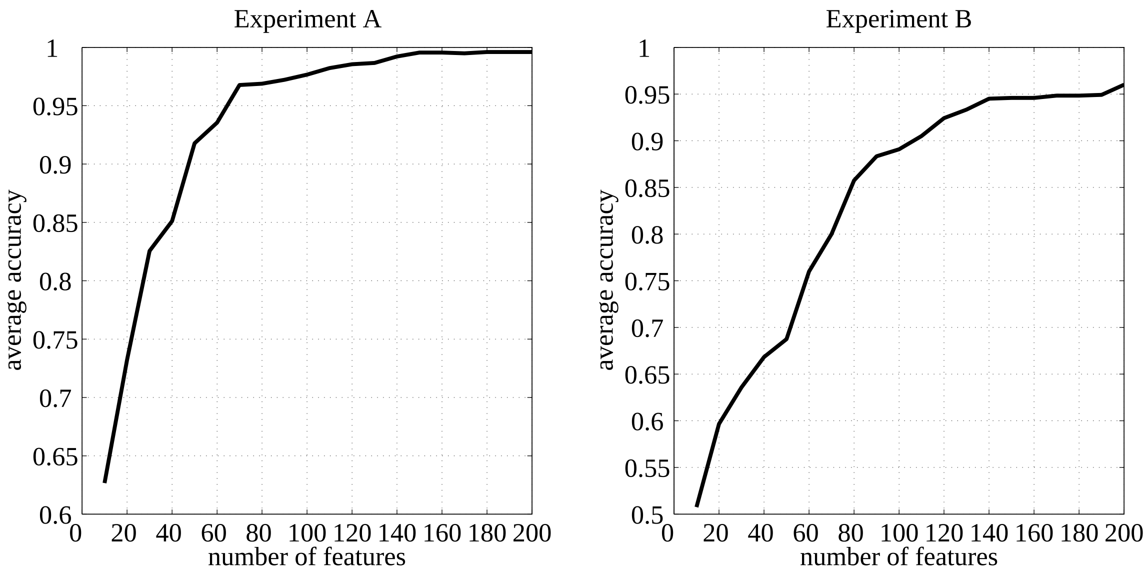


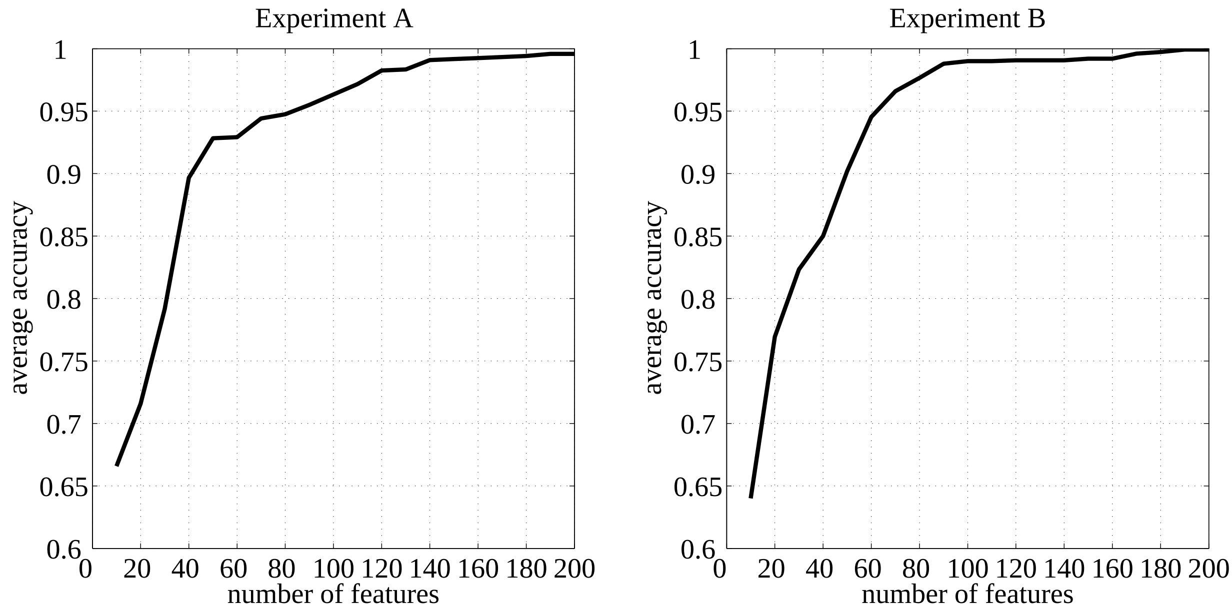
Table 3 Recognition results of LOS vs. NLOS with 150 features in Experiment A

Result\ class	*A1* (*LOS*)	*A2* (*NLOS*)	*A3* (*NLOS*)	*A4* (*NLOS*)
LOS	299	4	3	0
NLOS	1	296	297	300

Table 4 Recognition results of LOS vs. NLOS with 150 features in Experiment B

Result\ class	*B1* (*LOS*)	*B2* (*NLOS*)	*B3* (*NLOS*)	*B4* (*NLOS*)	*B5* (*NLOS*)
LOS	300	3	0	5	7
NLOS	0	297	300	295	293

Figure 7 Average recognition rate vs. number of features, when applying the method to identify different distances in NLOS



From Figures 6 and 7, we can tell that a positive relationship exists between the numbers of features and the recognition rates. When the numbers of features are larger than 80, both Experiments A and B achieve a good average recognition rate when identifying LOS and NLOS, which is no less than 95%. And after that point, the recognition rate upgrades very few with the increase of numbers of features. Moreover, from Figure 7, it indicates that when the number of features is larger than 140, there is also a recognition rate no less than 95% in both Experiments A and B, when identifying different distances in NLOS. In real applications, the number of features is easy to increase, for the reason that features are frequent points and easy to be selected.

Table 5 Recognition rates of different distances with 150 features in Experiment A

Distance	*A2 (%)*	*A3 (%)*	*A4 (%)*
Accuracy	99.33	100	98.00

Table 6 Recognition rates of different distances with 150 features in Experiment B

Distance	*B2 (%)*	*B3 (%)*	*B4 (%)*	*B5 (%)*
Accuracy	95.00	96.33	93.00	93.00

From Tables 3 and 4, it can be indicated that when the number of features is sufficiently large, the recognition rates of each dataset for LOS and NLOS classifying are all more than 97%(293/300). Tables 5 and 6 also indicate that this method has a good ability to discriminate different distances in the NLOS scene. It can also be told from Table 5 that although the positions between A3 (6.40 m) and A4 (6.82 m) are very close, this method can still have a very good performance, which means this method has a very good sensitive to even a very small distance.

In this method, once the training procedure is finished, the weight matrix $\overrightarrow{W}$ of RBF neural network is stored for identification. Then in the testing phase, when the testing bispectra of the testing data is calculated, it is very easy to pick out the selected bispectra frequency points to form the RBF neural network's hidden node output vector, and it takes only a few matrix multiplications to get the result. So the complexity of the algorithm majors in the calculation of bispectra. The application of higher order spectrum has long been long criticised for its cumbersome calculations. But by applying direct algorithm of non-parameter bispectrum estimation, it is able to apply this method to real systems, for the sake of FFT approach, which is the base of the estimation procedure, has been supported by most DSP chips.

5 Conclusion

This paper proposes a method of obstacle identification based on UWB and selected bispectra. This method is different from the existing radar system, and it focuses only on the received signal waveform. It needs no velocity or Doppler shift information of the target, nor the movement of the transmitter or the receiver. This enables the method to be applied to the normal WSNs without adding new equipment. Two groups of ultra-wideband out door obstacle identification scenes (LOS vs. NLOS and different distances) under foliage environment are measured. The distinguishing key features are extracted from the received signal and then the radial-basis function is established. The experiment results demonstrate that the detection and identification method of obstacle based on UWB and selected bispectra is effective for obstacle identification of both existence and the different positions of the target in foliage environment. And according to the experiment result, this method is sensitive to even a very small distance. Applying this method to identify more kinds of targets and considering the angle invariance will be the subject of further investigation.

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