High-resolution ranging method based on low-rate parallel random sampling

Jie Lin, Guangming Shi *, Xuyang Chen, Fei Qi, Li Zhang, Xuemei Xie

Key Lab. of Intelligent Perception and Image Understanding of Ministry of Education, Xidian University, China

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In this paper, we propose a low-rate high-resolution ranging method for UWB (up to several GHz of sampling rate) ranging system. It exploits compressed sensing (CS) theory and a parallel sampling ADCs structure based on random projection (PSRP). To guarantee the effective application of CS on the received signal, we construct a dictionary in which the atoms are time-shifted versions of the transmitted signal. Hence the received signal can be low-rate sampled by PSRP. For an UWB ranging system using PSRP instead of the newly proposed analog-to-information converter, it possesses the universality of dictionary atoms, lower sampling rate and better performance for noisy signal. Additionally, since the dictionary size in this work can be adjusted flexibly, a desired high resolution can be achieved. The simulation results confirm these advantages via a noisy received signal (SNR = 16 dB) which contains five target echoes. Though the received signal is sampled at less 10% of Nyquist rate, the probability of echo detection is over 95% and the distance resolution reaches the optimal of the conventional ranging method.

1. Introduction

In a ranging system, such as radar or sonar, high resolution is one of the most desired quality for target detection. Ultra-wideband (UWB) signals are usually adopted as the transmitted signal for their prominent ability of high resolution. However, with the conventional sampling techniques, the cost of analog-to-digital conversion increases dramatically with the signal bandwidth. And if the required sampling rate is up to several GHz, the high-rate analog-to-digital converters (ADCs) available only limit to flash ADCs. However the resolution of flash ADCs cannot be more than 8 bits due to the nonlinearity of structure. Thus, under the limitations of current semiconductor technology, it is unrealistic to achieve high-rate high-resolution digitization of an UWB signal using a single ADC chip. Hence some parallel sampling approaches were proposed to digitize UWB signals. Based on the hybrid filter banks (analog analysis filters and digital synthesis filters), Velazquez et al. [1] proposed a frequency-channelized receiver. Sampling a signal with an M-channel receiver, the sampling rate of each channel is 1/M of the aggregate sampling rate of the receiver. Whereas there are some problems including the uncertainties of the analog analysis filters and the low convergence speed, which make it difficult to apply the receiver. To overcome these problems, an oversampled channelized receiver [2] was proposed, which estimates the combined responses of the analysis filters and the propagation channel. In addition to these parallel techniques, a parallel sampling ADCs structure based on random projection (PSRP) was proposed in [3] to digitize UWB signal. With an M-channel PSRP, the sampling rate of each channel is 1/M of its aggregate sampling rate. However, all the above parallel sampling systems would result in enormous sample data which are unwieldy in applications.

Fortunately, in the last few years, some sampling schemes get considerable attentions for their ability to sample signals at sub-Nyquist sampling rate. For instance, for some signal classes which are nonbandlimited but have finite degrees of freedom per unit time, called the innovation rate, Vetterli et al. [4] suggested to uniformly sample these signal classes at the innovation rate. But this method needs to compute a reconstruction kernel that is infinite in size sometimes and may be intractable. For signals having a sparse representation in some transform domains, compressed sensing (CS) theory [5,6] indicates that such signals can be sampled with a random measurement matrix at a low rate, and then exactly recovered by optimization techniques. Moreover, in the framework of CS theory, Kirollos et al. [7] developed an analog-to-information conversion (AIC) structure to implement the random measurement of signal. The procedure of AIC consists of random...
modulation, filtering and sampling. The AIC was used in our former paper to sample UWB signal at a low rate [8]. Nevertheless as a random sampling approach for sparse signals, the AIC structure lacks universality due to the causality of the filter. That is to say, for the basis functions used to represent signal, if they are infinite-supported, the combined matrix1 would be uniformly random; Otherwise, the combined matrix would be sparse (strip-shaped), which degrades the performance of optimization with same amount of measurements. The use of filter causes difficulties in practical implement because the order of filter is usually over 10 for a satisfactory signal recovery. Another parallel structure is proposed to achieve spectrum sensing in Cognitive Radio [9]. Based on CS, this structure exploits the sparsity of signal at frequency domain to achieve sub-Nyquist sampling rate. 

In this paper, we propose a low-rate high-resolution ranging method for UWB radar or sonar systems, which utilizes the CS theory and the parallel sampling ADCs structure based on random projection (PSRP). Based on the known form of the transmitted signal, a dictionary is predesigned to represent the received signal sparsely, in which each atom is a time-shifted version of the transmitted signal. Thus the effective application of CS can be guaranteed. Using the PSRP, the measurements of the received signal are obtained at a low rate. With \(\ell_1\)-minimization algorithm, the coefficients of the received signal with respect to the constructed dictionary can be successfully recovered from the measurements. Due to the form of atoms, each recovered coefficient corresponds to the information of a target echo – location and amplitude. So all the target echoes can be detected readily. Because the distance resolution in target detection depends on the number of atoms in the dictionary, we can use more compact atoms (with smaller shift between the adjacent atoms) to achieve a higher resolution. In our method, the resolution can exceed the optimal resolution in the conventional ranging method. Moreover, since the PSRP is insensitive to the length of atoms, the combined matrix will be uniformly random. As a result, compared with a ranging system using the AIC, the sampling rate in our method is lower and the performance of recovery for noisy signal is better. The simulation results confirm that, for a received signal with five target echoes, the target detection can be achieved at the probability over 95%.

2. Compressed sensing and parallel sampling based on random projection

2.1. Review of compressed sensing theory

The theory of compressed sensing (CS) was developed by Candès, Romberg and Tao [5] and Donoho [6] in 2004. It indicates that, if a signal has a sparse representation in some transform domains, it can be sampled at a rate significantly lower than the Nyquist rate, but still can be reconstructed with overwhelming probability by optimization techniques. The transform domain can be represented by an orthogonal basis, a tight frame or an overcomplete dictionary. For a signal \(s \in \mathbb{R}^N\), it can be represented by a dictionary \(\Phi = [\phi_1, \phi_2, \ldots, \phi_M]\), formulated as \(s = \sum_{i=1}^{M} x_i \cdot \phi_i = \Phi x\), where \(x \in \mathbb{R}^M\) is the coefficients vector. The columns of the dictionary \(\phi_i \in \mathbb{R}^N, i = 1, \ldots, M\), are called atoms. If the vector \(x\) has only \(S (S \ll M)\) nonzero entries, the signal \(s\) is defined to be \(S\)-sparse with respect to the dictionary \(\Phi\). An \(S\)-sparse signal \(s\) can be randomly measured by a measurement matrix \(\Psi \in \mathbb{R}^{m \times N}\), \(S < m < N\), producing the measurements \(y \in \mathbb{R}^m\), i.e.,

\[
y = \Psi s = \Psi \Phi x = Ax.
\]  

where \(A = \Psi \Phi\) is named as the combined matrix in this paper. According to CS, any matrix which obeys “restricted isometry principle” (RIP) [10] can act as a measurement matrix. The “RIP” guarantees the signal recovery possible even when the measurements are noisy [11]. Actually, most of the random matrices satisfy the “RIP” with overwhelming probability.

From (1), it can be found that the recovery of a signal from the measurements is an underdetermined problem. Some algorithms were developed to find the sparsest solution as the recovered vector \(x\), mainly including greedy algorithms [12–14] and convex programming [15–18]. The greedy algorithms usually require the knowledge of sparsity of the solution in advance and they have difficulty in distinguishing two closely spaced atoms in a dictionary. \(\ell_1\)-minimization algorithms do not require the knowledge of sparsity and guarantee the optimal solution. Hence in this paper, we suggest to utilize the \(\ell_1\)-minimization algorithm to recover the signal [6]:

\[
\min_{x} \|x\|_1 \quad \text{s.t.} \quad y = \Psi \Phi x,
\]

where \(\|x\|_1 = \sum_{i=1}^{M} |x_i|\). This \(\ell_1\)-minimization problem, also well known as the basis pursuit (BP) [19], can be solved effectively by linear programming, such as simplex algorithm and interior-point algorithm. If the measurements are with noise, the signal coefficients can be recovered by solving \(\ell_1\)-regularized least-squares problem [18]:

\[
\min_{x} \frac{1}{2} \|\Psi \Phi x - y\|_2^2 + \lambda \|x\|_1,
\]

where \(\lambda > 0\) is a regularization parameter. To recovery an \(S\)-sparse signal successfully, the amount of measurements \(m\) should satisfy \(m \geq C S \log N\), where \(C\) is a positive constant, \(N\) is the signal length and \(\mu\) is the coherence of the combination matrix \(A\) [20]. The coherence of a matrix \(A = [a_1, a_2, \ldots, a_M]\) is defined as

\[
\mu = \max_{i \neq j} \frac{|a_i \cdot a_j|}{\|a_i\|_2 \cdot \|a_j\|_2}.
\]

2.2. Parallel sampling ADCs based on random projection

The diagram of the sampling process in parallel sampling ADCs based on random projection (PSRP) [3] is shown in Fig. 1. The main components include mixers, integrators and ADCs. An input signal is projected onto the random signals by being mixed with the random signals and then integrated with the integrators, generating the projection coefficients. Then a set of ADCs are used to sample and quantize the projection coefficients, producing the measurements of input signal. The random signals used to mix the input signal are generated by the maximal-length linear feedback shift registers (MLFSR) [21]. The MLFSR can generate pseudo-random (+1, −1) sequence with zero average. The generated sequence is actually determined by the start-state called “seed”, thus it is pseudo-random. With the same seed, the MLFSR can generate the same sequence repeatedly. And the implement of MLFSR is very common. To synthesize the signal from the measurements, for an arbitrary signal, the Sinc function interpolation is applied; for a sparse signal, the optimization is adopted.

The PSRP scheme was proposed as a universal sampling technique for wideband signal. Because of the utilization of random signals on which an input signal is projected, the PSRP can be used to get the measurements of analog signal in the framework of CS. Unlike the AIC [7], when the PSRP is used to implement the measurement process in CS, the combined matrix is always uniformly random, whether the basis functions (or the dictionary atoms) for signal representation is infinite-supported or not.

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1 The combined matrix is the product of the measurement matrix and the matrix of basis.
3. High-resolution ranging method with low sampling rate

A novel ranging method with the properties of low sampling rate and high resolution is proposed in this section. First, based on the known transmitted signal, we construct a dictionary to get a sparse representation of the received signal. Then the received signal is measured at a low rate with the PSRP structure. At last, by solving an optimization problem, we can easily achieve the high-resolution target detection.

3.1. The construction of sparse dictionary

In this paper, we focus on a situation where the transmitted signal denoted as $s(t)$ is finite-supported and each target is stationary which can be modeled as a collection of point-scattering centers. Regardless what the particular waveform of the transmitted signal is, the reflected echoes from stationary point-scattering targets can be modeled as the scaled, shifted versions of the transmitted signal. Thus, the model of the received signal $r(t)$ can be formulated as

$$r(t) = \sum_{i=1}^{S} \alpha_i s(t - \tau_i),$$

where $S$ is the number of target echoes and the sets $\{\alpha_i\}$, $\{\tau_i\}$, $i = 1, 2, \ldots, S$, represent the amplitude and the location of target echoes, respectively.

To low-rate sample the received signal in the framework of CS, we first need to find an appropriate transform domain to sparsely represent the received signal. For the received signal modeled as (5), we construct a dictionary $\Phi = \{\phi_i(t), \ i = 1, \ldots, K\}$ in which each atom $\phi_i(t)$ is with form of

$$\phi_i(t) = s(t - i \cdot \Delta t), \ \ i = 1, \ldots, K,$$

where $\Delta t$ is the time interval of two adjacent atoms and $K$ is the number of atoms, i.e., the dictionary size. The atoms in the dictionary are uniformly-spaced, each atom $\phi_i(t)$ is a time-shifted version of the transmitted signal, with shift-amount being $i \cdot \Delta t$. If the received signal $r(t)$ in (5) is sampled at the Nyquist rate $f_s$, the discrete signal is denoted as $r(n) \in \mathbb{R}^N$. The interval of samples is $\Delta T = 1/f_s$. We assume the interval $\Delta t$ between two atoms in the dictionary satisfy the following constraints: $\Delta t \leq \min_{i,j=1,\ldots,S,i\neq j} |\tau_i - \tau_j|$ and $\Delta t \leq \Delta T$. The first constraint makes sure the interval of the adjacent atoms is less than the minimal interval of any two echoes in the received signal. The second constraint guarantees we can find an atom in the dictionary to match an echo at any location in a discrete received signal. Thus, for the representation of the received signal under consideration, the constructed dictionary is complete. The received signal $r(t)$ can be represented by the dictionary, i.e.,

$$r(t) = \sum_{i=1}^{K} x_i \phi_i(t),$$

where $x_i, \ i = 1, \ldots, K$ are the coefficients and we define $x = [x_1, x_2, \ldots, x_K]$ as the coefficient vector. Because the amplitude of any existing target echo is positive, all the entries of the coefficient vector $x$ are nonnegative. From (5) and (7), it can be found that, if the number of target echoes is far less than the dictionary size, i.e., $S \ll K$, the received signal is $S$-sparse with respect to the dictionary $\Phi$. So we call this dictionary the sparse dictionary for the received signal.

3.2. Low-rate high-resolution ranging system

In ranging systems, about the discrete received signal $r(n)$ introduced in Section 3.1, the following facts are well recognized:

1. In most applications, the number of target echoes in range is extremely small compared with the length of the discrete signal $r(n)$.

2. The information of targets is concentrated on the location and the amplitude of echoes.

Based on these facts, the sparsity of the received signal in (5) with respect to the dictionary constructed by (6) can be well guaranteed. So according to the CS theory, the received signal can be sampled at a low rate, and then recovered successfully by optimization.

Based on all the analysis, a ranging system with the properties of low sampling rate and high resolution is developed in the framework of CS, shown in Fig. 2. In this ranging system, the measurements $y$ are obtained by sampling the input signal $r(t)$ at a low rate with PSRP. Then, the coefficients $x$ of the received signal can be recovered by optimization algorithms. At last, the target detection is implemented based on the recovered coefficients.
More specifically, the construction of dictionary in Fig. 2 is an “off-line” process. Based on the known transmitted signal, the sparse dictionary $\Phi$ is constructed by (6) in advance. Hence, the computation complexity of generating the atoms will not burden the “sampling-recovery” implementation. For the PSRP module, benefiting from the sparsity of the received signal, the channel number is set to be far less than the length of signal $r(n)$. Hence the sampling rate of the received signal is much lower than the Nyquist rate. Using the random signals generated by PSRP, the measurement matrix $\Psi$ is obtained, so does the combined matrix $A = \Psi \Phi$. Both two matrices are not related with the input signal.

The interval of two adjacent atoms $\Delta t$ is an important parameter of the dictionary and here we explain how to determine it. To represent a received signal within a given time support by the constructed dictionary, all the atoms must spread over the support of signal. Thus the interval $\Delta t$ is inverse proportional to the dictionary size $K$, i.e., $K \propto 1/\Delta t$. Because $\Delta t$ determines the resolution of signal decomposition, and the target detection is totally based on the signal coefficients, the decrease of $\Delta t$ will lead to the increase of the distance resolution for target detection, i.e., resolution $\propto 1/\Delta t$. For a special case of $\Delta t = \Delta T$, the distance resolution of our method equals the optimal resolution of the conventional ranging method in which a matched filter is utilized to locate the target echoes. It is worth noting that, a higher resolution requires more compact atoms in the dictionary, i.e., a bigger dictionary size. However, a dictionary with a bigger size requires more storage, and also increases the ambient dimension of the optimization problem for signal recovery. Hence, the dictionary size and the distance resolution should be balanced appropriately in practical applications.

As we mentioned in the last of Section 3.1, the coefficients $x_i$, $i = 1, \ldots, K$, in (7) are nonnegative real. This is different from the general case of CS in which the sparse signal under consideration is assumed to be real. In [22], Donoho asserted that in CS theory, for Gaussian measurement matrix, if the sparsity of the sparse nonnegative solution satisfies $S \leq 0.558 m$, it can be found by solving $\ell_1$-minimization problem. And a conditioned OMP was proposed by Bruckstein et al. in [23] to find the sparsest solution of an underdetermined system with the nonnegative constraint. For a special case of the measurement matrix being the adjacency matrix of expander graphs, a fast algorithm is proposed in [24] to find the nonnegative sparsest solution of the underdetermined system. In this paper, the measurement matrix is not an adjacency matrix and the sparsity of the received signal is not known, so the $\ell_1$-minimization algorithm is used to solve the underdetermined system with nonnegative constraint. The $\ell_1$-minimization problem for the recovery of the coefficient vector $x = [x_1, x_2, \ldots, x_K]$ of noise-free signal and noisy signal are formulated as:

\[
\text{(Noise-free)} \quad \min \|x\|_1 \quad \text{s.t.} \quad y = \Psi \Phi x, \quad x_i \geq 0, \quad (8)
\]

\[
\text{(Noisy)} \quad \min \frac{1}{2} \|\Psi \Phi x - y\|_2^2 + \lambda \|x\|_1, \quad \text{s.t.} \quad x_i \geq 0. \quad (9)
\]

These problems can be effectively solved by some state-of-the-art solvers, such as 11_Ls [25] or YALL1 [26]. In this paper, the 11_Ls solver is used to recover the coefficients of signal. For a successful recovery of $S$-sparse signals from the random measurements, the amount of measurements $m$ required by a nonnegative signal ($m = 25 \times K$ [22]) is less than that required by a real signal ($m \approx 35 \times K$ [27]). Hence, benefiting from the constructed sparse dictionary, the nonnegativity of signal coefficients will lead to the decrease of the necessary measurements, relative to other cases in which a general time-frequency dictionary is used to represent the signal.

### 3.3 Analysis of the combined matrix

Considering the combined matrix influences the performance of the proposed ranging method, we analyze the property of the combined matrix. In order to give a good explanation, a ranging method using AIC (AIC-RM) [8] is used as a comparison to the ranging method using PSRP (PSRP-RM) in Fig. 2. For a given sparse dictionary composed with finite-supported atoms, the combined matrices in the two methods are presented in Fig. 3. We analyze the two combined matrices from following three aspects: the uniform randomness, the coherence and the condition number.

To begin with the analysis of uniform randomness, we can see that, for the combined matrix of AIC-RM in Fig. 3(a), the nonzero values are concentrated in the diagonal; for the combined matrix of PSRP-RM in Fig. 3(b), the nonzero values are uniformly randomly distributed in the whole matrix. Measurement using a uniformly random matrix can preserve more information of signal than that using a sparse matrix, which is illustrated in Fig. 4. A tested sparse signal in Fig. 4(a) is multiplied by one of the rows in the two combined matrices in Fig. 3, generating the products shown in Figs. 4(b) and 4(c) respectively where the nonzero entries mean the preservation of signal information. From the measurement process in (1), it can be found that each measurement is the integration of the product of the sparse vector and one of the rows in the combined matrix. Thus, based on Figs. 4(b) and 4(c), we can draw a conclusion that, in PSRP-RM, every measurement contains much more information of signal. Consequently, PSRP-RM will

outperform AIC-RM with the same amount of measurements for signal recovery.

Then, we analyze the coherence $\mu$ of a matrix defined in (4) which reveals the vulnerability of the matrix. A high coherence caused by two similar columns in the combined matrix may degrade the performance of the optimization technique for signal recovery [28]. So, for a given dictionary, a lower coherence is better for the optimization algorithm to search the correct solution. Computing the coherence of matrices in Fig. 3, we find that the coherence $\mu$ of the combined matrix of PSRP-RM is indeed smaller than that of AIC-RM ($\mu$: 0.87 vs. 0.98). It is worth noting that the coherence of the combined matrix depends on the similarity of atoms in the dictionary, which is very strong in our proposed dictionary since each one is the shift version with small displacement of the adjacent one.

At last, we calculate the condition number of the combined matrix in the view of numerical analysis. The condition number of a matrix measures its stability or sensitivity to the digital computation. A small condition number of a matrix means that the matrix is well-conditioned, while a high condition number means that the matrix is ill-conditioned. For reference, the condition number of an orthogonal matrix is 1. For the two matrices in Fig. 3, the condition numbers of PSRP-RM and AIC-RM are 2.856 and $5.695 \times 10^4$, respectively. Clearly, the combined matrix of AIC-RM is ill-conditioned, while the combined matrix of PSRP-RM is well-conditioned. Thus PSRP-RM is more stable than AIC-RM to the digital computation.

4. Simulation results and discussion

In the proposed ranging method, the detection probability of target echoes is used to evaluate the ranging performance. Because of the form of the atoms in the dictionary, for a noise-free signal, the probability of echo detection (both location and amplitude) exactly equals the probability of signal recovery. As for the noisy signal, an exact signal recovery is generally impossible due to the influence of noise. In this case, the detection probability of targets’ location is used to evaluate the performance. And the amplitude error of the signal coefficients is also calculated as an additional reference.

In the following simulations, a received signal including five target echoes is tested. If the received signal is sampled at the Nyquist rate $f_n$, the corresponding discrete signal has 1024 samples. And the interval of two adjacent atoms in the dictionary is set to be $\Delta t = \Delta T = 1/f_n$. Each simulation of signal recovery is repeated 100 times and the detection probability is the percentage of successful recovery.
To begin with the noise-free case, the detection probability of the received signal is presented by a line with circles ("•") in Fig. 5. It can be found that, for the $S$-sparse (here, $S = 5$) signal, only 50 measurements are needed for the perfect echo detection. That is to say, the sampling rate in our method drops to about 5% ($50/1024$) of the Nyquist rate $f_s$. As a comparison, the probability of detection in AIC-RM [8] is also presented by a line with triangles ("△") in Fig. 5. It can be seen that for a perfect detection of target echoes, the number of measurements increases to 100 in AIC-RM. This is caused by the nonuniform randomness of the combined matrix in AIC-RM.

Next, for the case of noisy signal, the detection probability of target echoes’ location is calculated. Assume that the signal is polluted by Gaussian white noise. Before the detection of target echoes, a hard thresholding (e.g. 10% of the amplitude of the normalized transmitted signal) is implemented on the recovered coefficients of signal. Without loss of generality, for a noisy signal with SNR $= 20$ dB, we present the results of PSRP-RM and AIC-RM in Fig. 6. It can be seen that for a perfect detection of target echoes, the number of measurements increases to 100 in AIC-RM. This is caused by the nonuniform randomness of the combined matrix in AIC-RM.

Fig. 5. Noise-free signal.

Fig. 6. Noisy signal (SNR = 20 dB).

(a) The detection probability

(b) The error of coefficients

Fig. 7. The detection probability and coefficients error for signal with different SNR.

AIC-RM degrades obviously (about 13% ($130/1024$) of the Nyquist samples for the perfect detection), due to the poor property of its combined matrix.

The last but not the least, we analyze the robustness of the proposed ranging method to noise interference. Given a fixed number of measurements (say, 100), Fig. 7 presents the detection performance of PSRP-RM and AIC-RM for noisy signal. Fig. 7(a) shows the detection probability of target echoes for signals with different SNR values. And Fig. 7(b) presents the amplitude error of the recovered coefficients in $\ell_2$-norm form. As a reference, the $\ell_2$-norm of the true coefficients vector is 1.64. From Fig. 7(a), it can be found that the PSRP-RM works well when SNR $\geq 16$ dB, but the AIC-RM works well only when SNR $\geq 22$ dB. From Fig. 7(b), we can see that, for the recovered coefficients vector, the amplitude error in PSRP-RM is 8.7% ($0.143/1.64$) of the true coefficients when SNR $= 16$ dB. However, in AIC-RM, the amplitude error of the recovered coefficients reaches 32.5% ($0.533/1.64$) of the true coefficients even when SNR $= 22$ dB. Hence we can say that, in PSRP-RM, the recovered coefficients of signal are with better accuracy in both location and amplitude. This is because there are more signal information contained in the measurements of PSRP-RM than that of AIC-RM.
From above simulation results, it can be found that, due to $\Delta t = \Delta T$, the proposed method reaches the optimal resolution of the conventional ranging method. And the sampling rate is much less than the Nyquist rate of the received signal. Furthermore, compared with the ranging method using AIC, the proposed method has better robustness to noise and requires less measurements for a satisfactory signal recovery.

5. Conclusion

This paper introduced a ranging method with the advantages of low sampling rate and high resolution. In the proposed method, the construction of the sparse dictionary plays a very important role. The received signal is sparse with respect to the constructed dictionary, which makes it able to be low-rate sampled based on the CS theory. A high resolution can be achieved in the proposed ranging method by constructing the sparse dictionary with more compact atoms. The simulation results proved that, in the proposed method, the sampling rate is much lower than the Nyquist rate, also lower than that of the ranging method using AIC. Moreover, the distance resolution can achieve the optimal of the conventional ranging method easily. With the proposed ranging method, the high sampling rate caused by the digitization of UWB signal will no longer be the main obstacle in applications of high-resolution ranging.

References


Jie Lin was born in 1979. She is a Ph.D. student in Xidian University. Her research interests include intelligence signal processing, compressed sensing and its applications. E-mail: jilin@mail.xidian.edu.cn

Guangming Shi was born in 1965. He received the M.S. degree in Computer Control and Ph.D. degree in Electronics Science and Technology from Xidian University in 1988 and 2002, respectively. He is a professor in Xidian University. His research interests include intelligent signal and information processing and its applications and implementation.

Xuyang Chen was born in 1980. He received the Ph.D. degree in circuit and systems at Xidian University. His current research interests focus on optimization calculation, compressed sensing and its applications.

Li Zhang was born in 1968. He received the M.S. degree in Computer Science from Xidian University in 1996. His research interest is the implementation of complex digital signal processing.

Qi Fei was born in 1977. He got his Ph.D. degree from Tsinghua University in 2007. His research interests are visual tracking and information fusion.

Xuemei Xie was born in 1967. She received her M.S. degree in Electronic Engineering from Xidian University in 1994, and Ph.D. degree in Electrical & Electronic Engineering from the University of Hong Kong in 2004. Her research interests are digital signal processing, multirate filter banks, wavelet transform.