Counting Surrounding Nodes Using DS-SS Signals and De Bruijn Sequences in Blind Environment

Chirag Warty
School of Engineering
Uniersity of Colorado Boulder
Boulder, USA
chirag.warty@colorado.edu

Gorkem Secer
Department of EE Engineering
Bilkent University
Ankara, Turky
secer@ee.bilkent.edu.tr

Richard Wai Yu
System Engineer
NAVSEA, Port Hueneme
Los Angeles, USA
richard.yu@navy.mi

Susanna Spinsante
Dept. Information Eng.
Marche Polytechnic Univ.
Ancona, ITALY
s.spinsante@univpm.it

Abstract— **In recent years the technological development has encouraged several applications based on node to node communications without any fixed infrastructure. This paper presents preliminary evaluation of popular estimating techniques to populate active nodes in the neighborhood using De Bruijn sequences. They have much higher cardinality compared to any other family of binary sequences at a parity of length. This characteristic of De Bruijn sequences can be exploited to identify the presence of an active node in a dense surrounding, to assist the primary node in making intelligent decisions in a blind or foggy environment. The simulation model in this paper evaluates the use of eigenvalue estimation to estimate the spreading sequence among noisy signals, based on eigenvalues analysis techniques. The received signal is divided into windows, from which a covariance matrix is computed; the sequence can be reconstructed from the two first eigenvectors of this matrix, and that useful information, such as the desynchronization time, can be extracted from the eigenvalues.**

TABLE OF CONTENTS

1. INTRODUCTION

The Direct Sequence Spread Spectrum (DS-SS) has been widely used for military and commercial communication systems for several decades owing to its information assurance and low interception properties. DS-SS communication has many characteristics, such as wide spectrum, low power spectral density, confidentiality, anti-interference and ease of used in multiple access communication. Pseudonoise (PN) sequences are very important parameters in DS-SS communication systems, in which multiple users can share the same frequency band at the same time. It is of great significance to investigate the blind estimation of DS-SS signals, that is the condition that holds in non-cooperative scenarios [20]. In conventional cooperative applications, the transmitted information can be recovered with prior knowledge of the spreading waveform at the receiver. However, in non-cooperative applications such as node to node (N2N) communications, in an ad hoc environment the spreading waveform is unknown to the receiver and recovery of information has to be done in a blind fashion. Therefore, detecting and estimating a spreading waveform from intercepted DS-SS signals plays an important role in non-cooperative scenarios. The same technique used to estimate a spreading waveform in DS-SS may be applied in N2N communications for estimating the number of active nodes in the vicinity of a target (reference) node. In this context, the focus is not on recovering the specific PN waveform, but on understanding how many waveforms (i.e. active nodes) are in the surroundings of the receiver (target node).

At the same time, node safety is also increased by the ability to exchange information among nodes, where each node transmits a locally unique sequence. The issue of N2N communication is always married with concerns of privacy and license free spectrum to broadcast. Employing Spread Spectrum Pseudo Noise methods in Direct Sequence configuration on a ISM band overcomes this limitation. The specific PN sequence acts as the node signature. Due to their low probability of interception, these signals increase the difficulty of spectrum surveillance. The initial symbol of the PN sequence can be calculated by using the average cross correlation property after disaggregating the received signal into segments. As shown in [1] and [2] eigen a desired level of accuracy in a DS-SS signal. The received signal is divided into windows which can then be used to compute a covariance matrix. The PN sequence can be reconstructed using the two significant eigen vectors of the matrix, even when the dispreading sequence is unkown to the receiver [2].

DS-SS is a transmission technique in which a pseudo-random sequence, independent of information symbol, is employed as a modulation waveform to spread the signal energy over a bandwidth much greater than information signal bandwidth [2][3][4]. Due to increased bandwidth of the spread spectrum signal, the power spectral density is generally below the noise level [5]. In a synchronized system, at the receiver the signal is de-spread using a synchronized replica of the same PN sequence used at the transmitter. However, such a possibility does not exist in a blind environment, when the PN sequence used by the transmitter is unknown. Moreover, the longer the period of the pseudo random sequence, the closer the transmitted signal will be to a truly random wave and harder

978-1-4673-1813-6/13/$31.00 ©2013 IEEE.
[1] IEEEAC Paper #2059, Version 1, Updated 01/08/2013.

to detect [6][7]. In the technique proposed by Bouder et.al. [6] the received signal is sampled and divided into temporal windows, the size of which is the PN sequence period, which is assumed to have been estimated. This technique is much more computationally simple and easier to implement then the maximum likelihood (mL) estimation technique [Glisic].

A common limitation to face in DS-SS applications is the relatively small set of PN signatures available, of a given length, and able to satisfy precise requirements of auto- and cross-correlation properties. Classical maximal length sequences (the m-sequences) and Gold sequences, besides chaotic signals featuring very favorable auto-and cross-correlation properties have been considered. This paper explores the applicability of De Bruijn sequences over DS-SS channel, as an alternative to classical solutions. De Bruijn sequences have been studied for many years, and valued for their huge cardinality; some of the properties concerning their correlation features are discussed in [8], [9]. In a crowded N2N scenario we assume to adopt De Bruijn sequences in order to assign a different sequence to each node.

Tsatsanis et.al [10] have proposed a reliable method to recover the convolution of the spreading sequence and the channel response in multipath environments. Moulines et.al [11] use a multichannel identification technique based on the orthogonality property between the signal and noise subspaces. The paper is organized as follows: Section 2 briefly outlines the concept of populating the surrounding over a DS-SS channel using De-Bruijn sequences. Section 3 reviews the known correlation properties of De-Bruijn sequences for N2N communications. Section 4 provides a preliminary evaluation of the estimation techniques used to recognize the node signature, and Section 5 is devoted to performance analysis, accompanied with simulations about the eigen value estimation technique applied.

2. Spread Spectrum System Model

In Spread Spectrum (SS) communication systems, the performance of synchronization and transmission highly depend on the selection of the pseudonoise (PN) sequences, especially under lower SNR conditions, and it is very difficult to demodulate and recover information without knowledge of the original PN sequence [12]. In the DS-SS transmission herein considered, the PN code generated at the modulator is a De Bruijn spreading sequence or a Gold code. In a practical system, the bandwidth expansion factor, which is the ratio between the chip rate Fc and the symbol rate FS, is usually an integer [12]. At the modulator block, Quadrature Phase Shift Keying (QPSK) modulation is introduced to shift the phase of the PSK signal at the chip rate FC, a rate that is an integer multiple of the symbol rate FS [12].

Considering a vehicular scenario, we want to estimate the DS-SS signals received by each vehicle, in order to evaluate how many surrounding vehicles are present. While sequence estimation algorithms are usually applied to identify the specific sequences, that are necessary to properly de-spread and demodulate the received DS-SS information bearing signals, in this case the focus is more on counting how many different sequences each receiver is able to recognize, that correspond to as many surrounding vehicles. Fig. 1 shows a sample road scenario: each vehicle may intercept DS-SS signals coming from surrounding vehicles. By counting how many different spreading codes may be identified, the target vehicle may estimate how crowded is the environment around itself, and take proper countermeasures to reduce the risk of collisions, or improve the traffic dynamics.

Figure 1. System Model

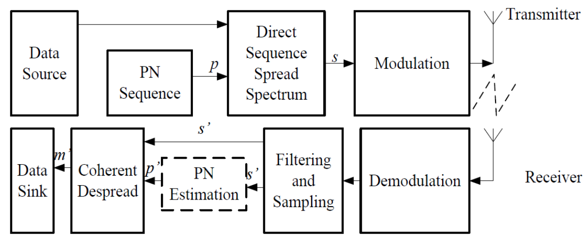

Figure 2. Angle of arrival of the signals at the transmitter

The general DS-SS system model is shown in Fig. 2, whereas Fig. 3 shows the same model for the case of K users. The k-th users data signal $b_k(t)$ is a sequence of unit amplitude, positive and negative, rectangular pulses of duration T. This signal represents the k-th users binary information sequence. The k-th user is assigned a code waveform $a_k(t)$ (the spreading code) which consists of a periodic sequence of unit amplitude, positive and negative, rectangular pulses of duration Tc. The k-th users code sequence has period $N = T/Tc$ so that there is one code period per data symbol. The data signal is then modulated onto the carrier, where θ_k represents the phase of the k-th carrier, ω_c represents the common center frequency, and P represents the common signal power. The delay T_k takes into account the fact that the transmitters are not synchronized. Finally, n(t) represents the channel noise, modeled as AWGN. The received signal r(t) is the input to a correlation receiver matched filter (optimum receiver).

Introducing the Gaussian approximation, the error probability at the receiver can be written as $1 - (SNR_i)$. The signal-to-noise ratio, SNR_i, at the output of the i-th correlation receiver is one of the most important performance measures

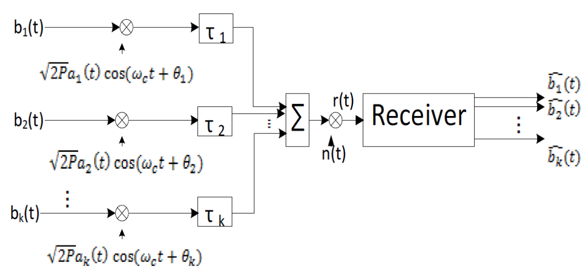

Figure 3. Detection Microstrip Antenna array (dimensions in mm)

and can be obtained with a reasonable amount of computation by evaluating the variance of the second term of the decision variable.
The received symbol r(t) is assumed to be a mixture of the original transmitted signal and the ambient AWGN element, and is represented by:

$$r(t) = s(t) + n_{awgn}(t) \tag{1}$$

$$r(t) = \sum_{k=1}^{k} b_k h(t - kT) + n_{awgn}(t) \tag{2}$$

where $n_{awgn}(t)$ is the noise coefficient at the receiver and the symbol period T corresponds to the spreading code period N-TC. The channel response can be expressed as proposed in [13]:

$$h(t) = \sum_{k=1}^{k} a_k p(t - kT_c) \tag{3}$$

where p(t) denotes the convolution of all the filter impulse responses at the transmitter.

Multipath Channel

with more than a single path linking the transmitter to the receiver are known as multipath channels. In a mobile ad hoc network, the multipath channel assumption is a realistic one, as not only transmitter and receiver may be moving with respect to each other, but also the surrounding environment may be changing, thus giving place to multipath propagation effects. The different paths might consist of several discrete paths, each one with different attenuation and time delay relative to the others, or they might consist of a continuum of paths. In the case under consideration, for simplicity reasons, we assume to have just two paths, the direct one and a single multipath. Assuming the time delay the signal incurs in propagating over the direct path is smaller than that incurred in propagating over the single multipath, the received signal may be written as:

$$\begin{aligned} r(t) = As(t)h(t)cos\omega_0 t + \alpha As(t-\tau)h(t-\tau) \\ cos(\omega_0 t + \theta) + n_{awgn(t)} \end{aligned} \tag{4}$$

where τ is the differential time delay associated with the two paths, and is assumed to be in the interval $0 \leq \tau \leq T$; θ is a random phase uniformly distributed in [0,2], and is the relative attenuation of the multipath with respect to the direct path. The output of the detection filter depends on the correlation function of the spreading sequence h(t). It is quite clear that given the scenario of interest (dealing with mobile nodes), the signal acquisition process, in terms of time, complexity, and size, should be as much rapid as possible, due to the node mobility, that may be also very quick. Also the signal tracking component is very important in keeping the offset time small. As a matter of fact, even a small value of τ may have a strong impact on the probability of error of the received data.

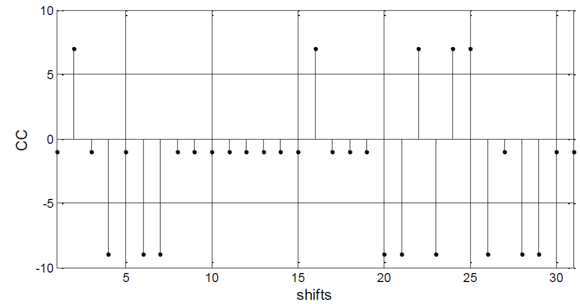

Figure 4. The S11 parameter of the detection antenna array

3. Spreading Codes

In order to evaluate the performance obtainable by using innovative sets of sequences like the De Bruijn ones, traditional codes are also applied as a reference. Among all the possible families of spreading codes that may be used, we refer to binary Gold codes, that are better described in the following.

A. Gold Codes

Binary Gold sequences are a well-known set of PN sequences, also used in wireless mobile communications (WCDMA) as scrambling codes, either in uplink (for separating the mobile stations) or in downlink (for separating the cells). Gold sequences are obtained by combining two m-sequences of length $N = 2^n - 1$, where n is the number of stages in the generating linear feedback shift register, from a set of so-called preferred m-sequences. Gold sequences exhibit a three-valued cross-correlation function, with values $\{-1, -t(n), t(n) - 2\}$, where t(n) is equal to:

$$t(n) = \begin{cases} \dfrac{2^{n+1}}{2} & \text{for odd } n \quad (5) \\ \dfrac{2^{n+2}}{2} & \text{for even } n \quad (6) \end{cases}$$

The auto-correlation function of Gold sequences is also a three valued function, with values $\{N, -t(n), t(n) - 2\}$.

The characteristic three-valued cross-correlation function of a pair of Gold sequences of length 31 (n = 5) is shown in Fig. 4. The number of Gold sequences, for a given N, is N + 2. Gold codes show good auto- and cross-correlation properties, particularly for large values of n. Further details on Gold codes may be found in [18].

De Bruijn Sequences

Binary De Bruijn sequences are a special class of nonlinear shift register sequences with maximal period $N = 2^n$: n is called the span of the sequence, i.e. the sequence may be generated by an n-stage shift register. In the binary case, the total number of distinct sequences of span n is $2^(2^((n-1))-n)$; in the more general case of span n sequences over an alphabet of cardinality, the number of distinct sequences is $\frac{\propto!^{n^{(n-1)}}}{\propto^n}$, In this paper we refer to binary De Bruijn sequences. The states $S_0, S_1, \ldots, S_{N-1}$ of a span n De Bruijn sequence are exactly 2^n different binary n-tuples; when viewed cyclically, a De Bruijn sequence of length 2n contains each binary n-tuple exactly once over a period. Being maximal period binary sequences, the length of a De Bruijn sequence is always an

Table 1. Length and total number of m-sequences, Gold, and de Bruijn sequences, for the same span value n ($3 \leq n \leq 10$).

	m-sequences		Gold		de Bruijn	
n	length	# seq.	length	# seq.	length	# seq.
3	7	2	7	9	8	2
4	15	2	15	17	16	16
5	31	6	31	33	32	2048
6	63	6	63	65	64	2^{26}
7	127	18	127	129	128	2^{57}
8	255	16	255	257	256	2^{120}
9	511	48	511	513	512	2^{247}
10	1023	60	1023	1025	1024	2^{502}

even number. When comparing the total number of De Bruijn sequences of length N to the total number of available m-sequences, or Gold sequences, similar but not identical length values shall be considered, as reported in Table I. The Table confirms the exponential growth in the number of De Bruijn sequences, at a parity of the span n, with respect to the other sequences.

In the vehicular context, it translates into the possibility of sharing the same signature generator across a very huge number of users, i.e. vehicles, and it may represent an attractive feature, when thinking about practical implementations. About the auto-correlation values $\theta_a(i)$ assumed by a De Bruijn sequence a of span n, for a given shift i, the known results are as follows:

$$\theta_a(i) - 2^n,\ i = 0 \tag{7}$$

$$\theta_a(i) = 0,\ 1 \leq |i| \leq n-1 \tag{8}$$

$$\theta_a(i) \neq 0,\ |i| = n \tag{9}$$

It is also known that $\theta_a(i) \equiv 0$ mod 4 for all i, for any binary sequence a of period N = 2n, with $n \geq 2$. As any binary De Bruijn sequence comprises the same number of 1s and 0s, when converted into a bipolar form the following holds:

$$\sum_{i=0}^{N-1} \theta_a(i) = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} a_j a_{j+1} = \sum_{j=0}^{N-1} a_j \sum_{i=0}^{N-1} a_{j+i} = 0 \tag{10}$$

A simple bound may be defined for the positive values of the correlation functions sidelobes, for any binary De Bruijn sequence a [7]:

$$0 \leq max\theta_a(k) \leq 2^n - 4\left[\frac{2^n}{2n}\right]^+,\ for\, 1 \leq k \leq N-1 \tag{11}$$

where $[x]^+$ denotes the smallest integer greater than or equal to x. In the case of binary De Bruijn sequences of span n = 5, the bound gives $0 \leq max\theta_a(k) \leq 16$. It is easy to prove that for an arbitrary pair of De Bruijn sequences a and b, including a = b, with span n and period N, the cross-correlation function $\theta_{ab}(k) = \sum_{i=0}^{N-1} a_i b_{i+k}, for 0 \leq k \leq N-1$, exhibits the following properties:

$$\theta_{ab}(k) = \theta_{ab}(N-k),\ for\ 0 \leq k \leq N-1$$

$$\sum_{k=0}^{N-1} \theta_{ab}(k) = 0 \tag{12}$$

$$\theta_{ab}(k) = 0\ mod\ 4,\ for\ n \geq 2, \forall k$$

For the cross-correlation function of a pair of De Bruijn sequences a and b $(a \neq b)$ with span n, the following bound holds: $-2^n \leq \theta_{ab}(k) \leq 2^n - 4,\ for\ 0 \leq k \leq N-1$

De Bruijn sequences may be piecewise orthogonal, i.e. it is possible to find two sequences having null cross-correlation for several values of the shift parameter k. On the other hand, it is also possible that two De Bruijn sequences have an absolute value of the cross correlation equal to 2^n for some shift k (e.g. complementary sequences for k = 0), as stated by the bound equation above. This variability in the behavior of the cross correlation may affect the performance of a multi user system, if the spreading sequences associated to each user are chosen randomly from the whole set of span n sequences. This also motivates the need for a proper selection criterion to be applied on the whole set of sequences, in order to extract the most suitable spreading codes to use.

4. Sequence Estimation and Counting

In the proposed scheme each node tries to detect the presence of the DS-SS transmission, while estimating it to a certain degree of accuracy in the received signal. Each node ignores the actual identity of the surrounding nodes while populating its surrounding in a blind environment. The receiver exploits the fact that the transmitter signal statistical properties [12]. The population density of surrounding nodes can be estiated as proposed by the Bouder and Burel in [13][14].

In a conventional scenario where the signal and noise frequencies vary, general filters can be used to separate the message from the ambient noise. However in a DS-SS environment the signal is specially built to be identical to the ambient noise: this makes it more complex to detect and separate the original transmission from the received signal. In the eigenvalue analysis technique the detection relies on the fluctuations of autocorrelation estimators, instead of autocorrelation itself. Even though the autocorrelation of a DS-SS signal is identical to that of the noise, the fluctuations vary by a significant degree [9]. To compute the autocorrelation fluctuations in the received signal y(t), the same is divided into U non-overlapping temporal windows. Each window comprises of few symbols in a window duration of T_W. When the autocorrelation estimator is applied to these windows we get:

$$\widehat{R^n_{yy}}(\tau) = \frac{1}{T_w} \int_{t_p}^{t_p+t_w} y(t)y^*(t-\tau)dt \tag{13}$$

Aggregating all the windows in the received signal, the second order moment of the estimator is given by:

$$\rho(\tau) = \frac{1}{U} \sum_{p=1}^{U} |\widehat{R^n_{yy}}(\tau)|^2 \tag{14}$$

As shown in Fig. 3 the antenna array is 2x1 elements and it is mounted over a Rogers RT/duroid 6002 with relative permittivity of 2.94 and thickness of 1.524 mm and at its bottom a ground plane is used. The design was simulated using high frequency structural simulator (HFSS) [**?**] and the results are shown in Figs. [4] and [5]. At the receiver, the

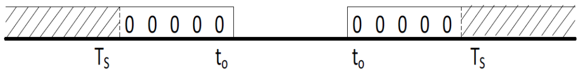

Figure 5. Vector composition of PN sequence

incoming signal can be represented as

$$y(t) = s(t) + n_{awgn}(t) \tag{15}$$

where $n_{awgn}(t)$ is the ambient noise (AWGN) and s(t) is the original transmitted DS-SS signal. In case of a blind environment, the received signal is to be detected in a non-cooperative fashion where no prior information is available. As proposed by Burel in [9] to compute the fluctuations, the received signal is divided into temporal windows. The correlation for a single n-th window can be computed as,

$$\widehat{R_{yy}^{n}} = \frac{1}{T_w \int_0^{T_w} y(t)y^*(t-\tau)dt} \tag{16}$$

If the correlation relationship is to be applied to the overall length of the received signal, i.e. to U windows, we get

$$\rho(\tau) = \hat{E}\{|\widehat{R_{yy}^{n}}(\tau)|^2\} = \frac{1}{U}\sum_{n=0}^{U-1} |\widehat{R_{yy}^{n}}(\tau)|^2 \tag{17}$$

where $\rho(\tau)$ is the degree of fluctuations in the autocorrelation of $(\widehat{R_y y})(\tau)$. Due to the fact that the DS-SS signal and noise exhibit completely different correlation properties, that overall signal can be represented as:

$$\widehat{R_{yy}}(\tau) \approx \widehat{R_{ss}}(\tau) + \widehat{R_{nn}}(\tau) \tag{18}$$

$\widehat{R_{ss}}(\tau)$ is the correlation of the transmitted DS-SS signal and $\widehat{R_{nn}}(\tau)$ is the channel noise correlation. As discussed in Section 5, the simulation results show the detection of the PN sequence with a sufficient accuracy to estimate the number of nodes in the surrounding. Lets go a step further and try to roughly estimate the detected sequence so as to estimate the chance of erroneously double counting the same sequence. The covariance matrix can be represented as:

$$R = E\{\overline{x} \cdot \overline{x}^2\} \tag{19}$$

As mentioned before the symbol duration is assumed to be identical to the window duration (Tw) and the symbol is said to be transmitted completely during a single window, with each symbol having a standard variance of ρ_S^2. If x is the content of a window, we have:

$$\overline{x} = C_m h_0 + C_{m+1} h_{-1} + n_a wgn \tag{20}$$

where $n_a wgn$ is the white noise, h_0 is the vector comprised of the end portion of the PN sequence followed by zeros, h_{-1} is the vector comprised of zeros followed by beginning of a new PN sequence, as shown in Fig.5.

Substituting the expression of each window content, the covariance matrix can be roughly estimated as:

$$\hat{R} = \frac{1}{U}\sum_{n=1}^{U} x_m \cdot x_m^H \tag{21}$$

5. Performance Analysis

In low SNR conditions (typical of Spread Spectrum communications), the inconsistency between estimated and original PN sequence causes the estimation error, which directly affects the transmission performance of the DS-SS system. The estimation of the PN sequence is more accurate, and the performance is improved, as the number of received chips increases. As a matter of fact, increasing the spreading rate through the use of more chips per data symbol, also increases the SNR per symbol, in additive white Gaussian noise (AWGN). However, in a time-varying multipath channel, the actual gain depends upon the stability of the propagation environment. If the channel changes appreciably during one symbol period, the gain of the receiver will be reduced, ultimately resulting in a net loss when the length of the spreading code is increased over a certain value. The spreading code must be longer than the multipath delay in order to avoid inter-symbol interference after de-spreading. However, to achieve the spreading gain, the channel must be stationary over the code length. In a non-stationary environment, a longer code leads to larger phase and multipath variation over a code period, thus reducing the achievable spreading gain.

Evaluation of computational complexity

Assuming the transmitted data length F is known, the length of the DS-SS signal after spreading with the N-length PN sequence is $F \cdot N$. The multiplying and adding times $(N_{mu}\ and\ N_{ad},\ respectively)$ required to estimate the PN sequence, referred to the existing Eigen Value Decomposition (EVD) algorithms [8][9][16][17] may be derive as:

$$N_{mu}(2N) = 2N \times 2N \times \frac{FN}{2N} = 2FN^2 \tag{22}$$

$$N_{ad}(2N) = 2N2N\left(\frac{FN}{2N} - 1\right) = 2FN^2 - 4N^2 \tag{23}$$

Based on the above analysis, the computational complexity of EVD algorithms is $O(FN^2)$. By comparing the number of operations requested by EVD algorithms, according to Eq. (22), in the hypothesis Gold, m-sequences, De Bruijn sequences of span n are used, it turns out that the choice of the specific PN sequence to use as spreading code does not affect the complexity of the EVD algorithm applied, in a significant way.

Detection of DS-SS signals

A SS signal is generated to be as much similar to noise as possible. As a consequence, the autocorrelation of a spread spectrum signal is close to a Dirac function, as well as the auto-correlation of a white noise (this is due to the pseudo-random sequence). It is possible to show, however, that the fluctuations of auto-correlation estimators allow to distinguish the useful signals from noise.

The received signal r(t) is divided into M non overlapping temporal windows, each of duration T large enough to contain a few symbols. An auto-correlation estimator is applied to each window:

$$\widehat{R_{yy}^{n}}(\tau) = \frac{1}{T}\int_{t_m}^{t_m+T} r(t)r^*(t-\tau)dt,\ m = 1\ldots M \tag{24}$$

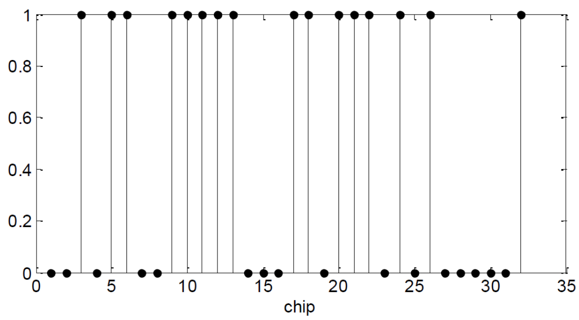

Figure 6. Sample binary De Bruijn sequence of length 32

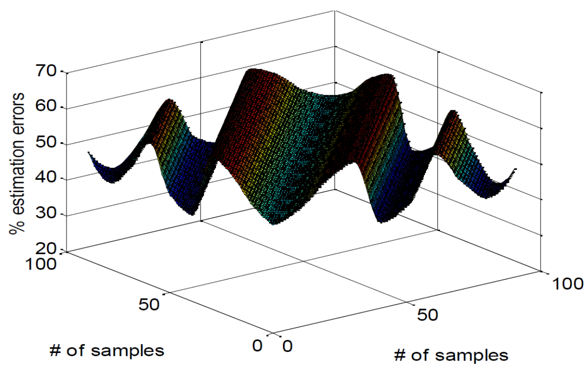

Figure 7. Percent estimation error in the case of Gold codes

and its second order moment computed:

$$\rho(\tau) = \frac{1}{M} \sum_{m=1}^{M} |\widehat{R_{yy}^{n}}(\tau)|^2 \tag{25}$$

By comparing the different fluctuations of the estimator when applied to a "noise only" case, and to a "noise plus signal" case, it is possible to detect the presence of a DS-SS signal. The same process allows also to estimate the PN sequence period, by locating the auto-correlation peaks.

Here, in DS-SS coding the modulation is done by modulating a sinusoidal wave in using a continuous form of pulse strings of pseudonoise coding (1's and 0's). On the other hand, due to the properties of cross-correlation properties, with the values of (2n) properties, and if n is large, this will indeed affect the performance of the system.

Fig.5 shows a sample binary De bruijn sequence of length 32 (span n = 5). For any value of n, De Bruijn sequences will contain 50% of either 1s or '0's'.

Once the DS-SS has been detected, the estimation process may take place. By resorting to the technique discussed in Section 4, the percent amount of correct estimations in presence of low SNR values, is obtained. Fig. 7 provides the results obtained when binary Gold codes of length 31 are used as spreading codes, whereas Fig. 8 refers to spreading by De Bruijn sequences.

It is possible to check how the estimation method applied may provide satisfactory results either in the synchronized and not-synchronized conditions. Fig.9 shows that in both cases, the percent amount of estimation errors is lower than 5%.

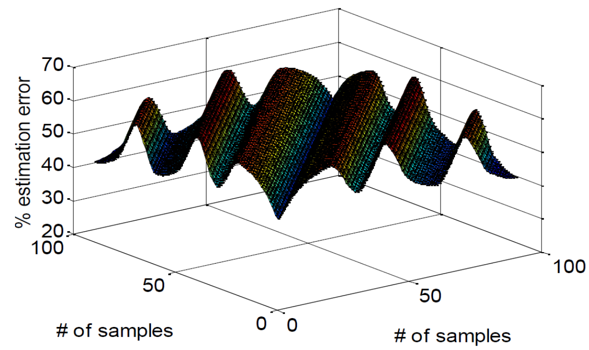

Figure 8. Percent estimation error in the case of De Bruijn codes

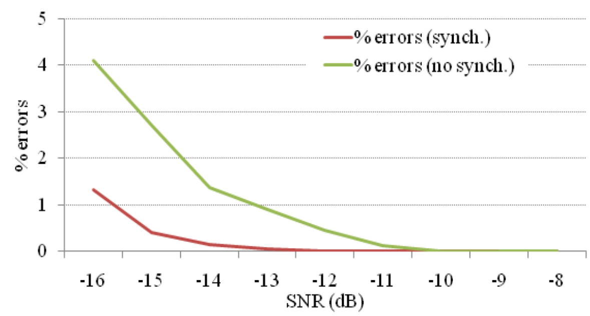

Figure 9. Percent amount of estimation errors for different SNR values, in synchronized and not synchronized conditions.

The low complexity estimation technique allows to identify the received spread signals and evaluate how many nodes are located in the vicinity of the target node.

The eigenvalues needed to reveal the spreading codes used, can be obtained by finding the correlation matrix of the output signal and using the following equation:

$$R_s q_m = \lambda q_m \tag{26}$$

Once all the eigenvalues are obtained, the peaks for the eigenvalues can be plotted by applying the fast Fourier Transform (FFT). Since the values will be in complex values, the next step is to find the magnitude of those values. The plotted magnitude values are the energy values (peaks) for those eigenvalues determined, as shown in Fig. 10.

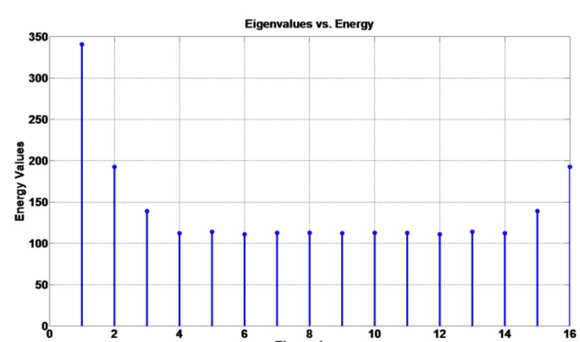

Figure 10. Estimated eigenvalues versus the energy of the symbol

6. CONCLUSION

This paper provides a simplified approach towards populating ones vicinity without the need of the high tech radar or GPS locators. The eigenvalue estimation technique is a reliable method that can be used to estimate a string of spreading codes in the DS-SS environment. Other techniques like RADAR can be used to detect nodes in the immediate surroundings, but they can only detect nodes that are unobstructed by other objects, and require much stronger computational capability. The counting technique enables the source to detect neighboring nodes even when they are obstructed by other nodes, while preserving the identity of the node. The counting method is not meant for location detection but is targeted towards estimating network density, as in case of mobile Ad Hoc networks.

REFERENCES

[1] W. Liping, Z. Li and J. Li, C. Chen, ”A Blind Algorithm for Estimating Pseudo-noise Sequence of DSSS Signal in Lower SNR Conditions,” in 3rd International Congress on Image and Signal Processing, 2010.

[2] G. Burel and C. Bouder, ”Blind Estimation of the Pseudo-Random Sequence of a Direct Sequence Spread Spectrum Signal,” IEEE, pp. 967-970, 2000.

[3] H. Krim and G. Proakis, ”Smoothed Eigenspace-Based Parameter Estimation,” Automatica, vol. 30, no. 1, pp. 27-38, 1994.

[4] D.V. Sarwate, M.B. Pursley Cross-correlation Properties of Pseudo-Random and Related Sequences, Proceedings of the IEEE, vol. 68, no. 5, pp. 593619, May 1980.

[5] R. L. Pickholtz, D. L. Schilling and L. B. Milsten, ”Theory of Spread-Spectrum Communications - A Tutorial,” IEEE Transactions on Communications , Vols. COM-30, no. 5, pp. 855-884, 1982.

[6] C. Bouder, S. Azou and G. Burel, ”A Robust Synchronization Procedure for Blind Estimation of the Symbol Period and the Timing Offset in Spread Spectrum Transmissions,” in IEEE 7th International Symposium on Spread-Spectrum Technnology and Applications, Czech Republic , 2002.

[7] R. Gold, Optimal Binary Sequences for Spread Spectrum Multiplexing. IEEE Transactions on Information Theory, pp 619-621, 1967.

[8] F. S. Annexstein, Generating De Bruijn Sequences: An Efficient Implementation, IEEE Trans. Comp., vol. 46, no. 2, pp. 198200, Feb. 1997.

[9] G.L. Mayhew, Third Update of the Order 7 De Bruijn Weight Class Distribution, Proc. of 2007 IEEE Aerospace Conf., Big Sky (MT), March 3-10, 2007, pp. 16.

[10] M. K. Testsanis, G. B Giannakis. Blind Estimation of Direct Sequence Spread Spectrum signals in multipath. IEEE Proceedings of ASILOMAR-29. Pp 403-407, 1996.

[11] Moulines, E. Duhamel, P. Cardoso, J.-F. Mayrargue, S. ”Subspace methods for the blind identification of multichannel FIR filters,” Signal Processing, IEEE Transactions, vol.43, no.2, pp.516-525, Feb 1995.

[12] C. Bouder, S. Azou and G. Burel, ”Performance Analysis of a Spreading Sequence Estimator for Spread Spectrum Transmissions,” Journal of the Franklin Institute , vol. 341, no. 7, pp. 595-614, 2004.

[13] C. Bouder and G. Burel, ”Spread Spectrum Codes Identification by Neutral Networks,” Systems and Control: Theory and Applications, pp. 257-262, 2000.

[14] W. LiPing, Z. Li, J. Li and C. Chen, ”A PN sequence estimation algorithm for DS signal based on average cross-correlation and eigenanalysis in lower SNR conditions,” Science China - Information Sciences , vol. 53, no. 8, pp. 1666-1675, 2010.

[15] G. Burel, ”Detection of Spread Spectrum Transmissions Using Fluctuations of Correlation Estimators,” IEEE-ISPACS, no. 5-8, Nov 2000.

[16] G.L. Mayhew, Autocorrelation Properties of Modified De Bryijn Sequences, Proc. of 2000 IEEE Symposium on Position, Location and Navigation, San Diego (CA), March 13-16, 2000, pp.349354.

[17] Proakis, J.G., Digital Communications, McGraw-Hill, 1995.

[18] J. M. Holtzman, A simple, accurate method to calculate spread spectrum multiple-access error probabilities, IEEE Trans. Commun., vol. 40, no. 3, pp. 461-464, March 1992.

[19] C. J. Mitchell, T. Etzion, K. G. Paterson A Method for Constructing Decodable de Bruijn Sequences, IEEE Trans. Inf. Th., vol. 42, no. 5, pp. 1472-1478, Sep. 1996.

[20] F. Chiaraluce, E. Gambi, R. Garello and P. Pierleoni, performance of DSCK in multipath enviroments: a comparision with systmens using gold sequences, IEICE Trans. Fundamentals, vol. E85-A, no. 10, pp. 2354-2363, Oct. 2002.

BIOGRAPHY

Chirag Warty (PMP, CSM, MEng) is currently a IEEE Associate Member. He has been the associate editor for the IEEE Interface magazine since January 2009. He currently holds several positions on IEEE Study Groups and IEEE societies. He has been consultant for several projects, in India and in the US. He also leads several research teams across the globe. He has perused several academic degrees in India and United States with a BSEE from University of Mississippi with specialization in RF and wireless, Masters of Engineering from University of Illinois-Chicago, Master of Science in Applied Mathematics from Columbia University. He also has several graduate certificates in communications and signal processing from Cornell, UCLA and Stanford. His research interests include MIMO, software defined radio, OFDM and 4G technologies including game theory for terrestrial wireless and satellite clusters.

Gorkem Secer received B.Sc. and degree in Control Engineering from Istanbul Technical University (ITU), Istanbul, Turkey, in 2009. He is currently pursuing the M.Sc. degree in Electrical and Electronics Engineering at Bilkent University, Ankara, Turkey. He has been with Roketsan Missile Industries Inc. as an engineer since 2009. His research interests include control systems, mechatronics system design and signal processing.

Richard Wai Yu is a systems engineer with the United States Department of Navy (DoN) and specializes in RF communication system and digital signal processing. He has wide experience in embedded designs with FPGAs using MATLAB and Simulink. He has previously served on several projects related to power engineering, control systems and system engineering, where he played key part in systems planning, researching, designing and engineering in finished products of commercial and military grade. His interest include RF digital communication systems and digital filter design. He has a BSEE and MSEE from California Polytechnic University - Pomona and a graduate certificate in communications.

Susanna Spinsante (*Senior Member, IEEE*) received her PhD in Electronics, Informatics and Telecommunications in 2005, from Università Politecnica delle Marche, Ancona (Italy). Since then she has been a research fellow at the Department of Information Engineering of the same University, where she works on spread spectrum systems for communications and radar applications.