Blind Multiuser Data Estimation in Asynchronous and Unequal Power DS-SS Systems without any Prior Knowledge of Spreading Sequences

S. Ghavami [1*], H. Alikhanian [2*], B. Abolhassani[3*] and H. Saligheh Rad[4#]

Electrical Engineering Department, [*] Iran University of Science and Technology, [#]University of Pennsylvania

[*]Tehran, 16846, Iran. [#]Philadelphia, PA 19104, USA.

[1]sghavami@ee.iust.ac.ir, [2] hooman_alikhanian@ee.iust.ac.ir,[3]abolhassani@iust.ac.ir and [4]hamid.saligheh@gmail.com

Abstract— **In this paper, a two phase algorithm is proposed for both blind synchronization and data sequence estimation of all users without any prior knowledge about spreading sequences in asynchronous unequal power multi-user direct sequence spread spectrum (DS-SS) systems. In the first phase, for blind synchronization, an eigenvalue variation (EV) based method is proposed, which uses all estimated eigenvalues related to signal, which are discriminated from noise eigenvalues by a threshold. In this paper, is shown EV to be a powerful tool for blind synchronization in eavesdropping scenarios in which unequal power signals are received from users. In the second phase, for blind data sequence estimation of all users, a variable step-size independent component analysis (ICA) algorithm based on negentropy maximization of active users is proposed using subspace as a preprocessing step. There is no need to know any spreading sequences for data estimation of users. Computer simulations confirm much better performance by the proposed algorithm at the cost of some more complexity compared with that of using only a pure subspace algorithm. Moreover, we compare the performance of the proposed blind synchronization with that of a successive blind synchronization, and we show that the proposed method is much faster.**

Index Terms— **DS-SS, Blind synchronization, Blind sequence estimation, ICA, Negentropy, subspace estimation.**

I. Introduction

DS-SS signals have been used for secure communications, command and control for several decades [1]. In conventional multi-user DS-CDMA systems, the power received from each user is almost equal and the spreading sequence is known to the receiver for the despreading operation and data detection [2]. However in non cooperative contexts such as spectrum surveillance and eavesdropping, the power levels received from users are unequal and spreading sequences used by transmitters are unknown (as well as other transmitter parameters such as bit epochs of active users and duration of the sequences). Hence, it is almost impossible to estimate the data sequence when it is very difficult even to detect the presence of the signal and to synchronize the receiver without meeting the above two problems. In this paper, we propose an algorithm to overcome both problems.

Synchronizing a DS-SS receiver for the single user case, knowing the spreading sequence is addressed well in the literature [3-4]. In [5], maximum likelihood (ML) estimator, approximative maximum likelihood (AML) and multiple signal classification (MUSIC) algorithms are used for propagation delay estimation in multiuser asynchronous DS-CDMA systems. In that, ML estimator needs to test all possible transmitted bit sequence in order to perform a true ML estimation of the unknown parameter. AML algorithm finds estimates of all the delays simultaneously, but the AML cost function is highly nonlinear with many local minima and is therefore sensitive to correct initialization. Both ML and AML must know spreading sequences of all users for simultaneous delay estimation of active users. The MUSIC estimates delays one by one and it requires knowledge of the spreading sequences of the users whose delays are to be estimated. Moreover, [6] proposes a subspace-based channel estimation for CDMA communication systems, it dose not need to spreading sequences of other users' spreading sequence, but knowledge of desired user's spreading sequence is necessary.

In the case of no knowledge about the spreading sequence, synchronizing the receiver is addressed in [7] for a single user scenario, in [8] for two user scenario and in [9] for multi-user and multi-rate scenario but with perfect power control. Moreover, in [10] a method is presented for synchronizing a multi user system based on behavior of the maximum eigenvalues of received signal's estimated covariance matrix. But, in our paper, we will show that this method cannot synchronize signals of users in the unequal power scenario without any prior knowledge about both desired and interfering users' spreading sequences.

It is notable that the open literature is not equally rich for synchronizing a DS-SS receiver for a scenario in which multi users signals are received with unequal power and no knowledge about both desired and interfering users' spreading sequences. This scenario usually occurs in eavesdropping. In this case, for practical consideration, the spectrum surveillance receiver is far from the base station and it receives unequal power signals. In this scenario with unequal power DS-SS signals, received by an eavesdropping receiver that doesn't know the spreading sequences, successive detection is proposed in [11]. However, the computational complexity of this algorithm is too much, which makes it impractical for real-time applications. In [12], a classical method, which is based on subspace estimation, is used for the estimation of the data sequence. In this method, second order statistics (SOS) is used for the data estimation, however it needs to know the spreading sequence of the desired user. Moreover, using the subspace estimation alone results in low performance.

In this paper, a two phase algorithm is proposed for the synchronization and the data sequence estimation in the scenario of unequal received power from multi-users DS-SS signals and no prior knowledge of any spreading sequence. In the first phase, an eigenvalue (EV) based blind synchronization is used, which is shown to be a powerful and much faster tool for eavesdropping scenarios in comparison of [11]. This method uses all eigenvalues of the received signal. Therefore, the number of eigenvalues of the signal first must be determined. Using all eigenvalues of the signal is the main contribution of this paper in the first phase in relative to that of [10]. In the second phase, although the receiver is synchronized yet it doesn't have spreading sequences to detect data of each transmitted signal. So, a blind data sequence estimation is proposed in which a negentropy maximization is applied for the received signal from each active user. The negentropy maximization, which is an ICA based algorithm, uses fourth order statistics of the received signal. The novelty of the second phase is using a subspace based preprocessing process with variable step size to increase the performance of the ICA-based data sequence estimation. The preprocessing process is applied for before using the ICA based algorithm in the second phase. This reduces computational complexity of the ICA algorithm.

The remaining of the paper is organized as follows: Section II presents the system model and Section III describes the EV based blind synchronization method. Section IV presents the proposed subspace ICA based algorithm for blind sequence estimation. In Section V the performances of the proposed algorithms are evaluated via computer simulations and our conclusions will be drawn in Section VI.

II. System Model

We consider the uplink scenario of the asynchronous CDMA systems. The eavesdropper receives signals of K active users. The received signal is given by

$$r(t)=\sum_{k=1}^{K}\sum_{j=-\infty}^{+\infty}A_k d_k[j]h_k(t-jT_s-\tau_k)+n(t), \qquad (1)$$

where A_k, $d_k[j]$, T_s and τ_k are, respectively, the received amplitude, j^{th} data symbol, symbol period and delay of k^{th} user and $n(t)$ is additive white Gaussian noise and K is the number of active users. The $h_k(t)$ is expressed by

$$h_k(t)=N^{-1/2}\sum_{m=0}^{N-1}c_k[m]p(t-mT_c)\,, \qquad (2)$$

where N is the processing gain, $T_c=T/N$ is the chip time, $p(t)$ is the convolution of the chip pulse shaping waveform with channel filter (which represents the channel echoes) and receiver filter, with unit energy. $c_k[m]$ is the value of the m^{th} chip with $|c_k[m]|=1$. Data symbols $\{d_k[j]\}$ of different users are independent with identical distributions (i.i.d.). Also channel model is assumed to be slow flat Rayleigh fading, and thus, channel coefficients are likely constant in a processing window duration. This slow fading assumption is valid for the processing window of 1000 symbols which makes $1.575\,m\sec$ for the bit duration of $1.575\,\mu\sec$ and the maximum Doppler frequency of $1/(10\times1.575m\sec)=63.5Hz$. For estimating of covariance matrix of the received signal, we need the symbol time value that can be estimated blindly using [13]. Covariance matrix of the received signal can be calculated as bellow [9]

$$\mathbf{R}=\sigma_n^2\left\{\sum_{k=0}^{K-1}\beta_k\left\{(1-\alpha_k)\mathbf{v}_k^{\#}(\mathbf{v}_k^{\#})^{*}+\alpha_k\mathbf{v}_k^{\dagger}(\mathbf{v}_k^{\dagger})^{*}\right\}+\mathbf{I}\right\}, \qquad (3)$$

where β_k is defined as $\beta_k=\sigma_{sig_k}^2T\big/\sigma_n^2T_s$. T and $\sigma_{sig_k}^2$ are respectively the sampling period and power of the k^{th} user received signal. In addition $\sigma_{sig_k}^2=\sigma_{sig_t}^2\times\gamma_k^2$ where $\sigma_{sig_t}^2$ and γ_k^2 are, respectively transmitted signal power and channel coefficient power for k^{th} user. $\mathbf{v}_k^{\#}$ and $\mathbf{v}_k^{\dagger}$ are normalized eigenvectors of the received signal covariance matrix obtained using eigen-decomposition. Each asynchronous user produces two eigenvalues that are $\lambda_k^{\#}$ and $\lambda_k^{\dagger}$ with two corresponding eigenvectors $\mathbf{v}_k^{\#}$ and $\mathbf{v}_k^{\dagger}$, and each synchronous user produces one eigenvalue $\lambda_k^{\#}$ with the corresponding eigenvector is $\mathbf{v}_k^{\#}$. α_k is the time delay of k^{th} user with respect to the beginning of the processing window.

III. First Phase of The Proposed Algorithm

In this section, a new synchronization method based on eigenvalue variation in terms of time shifts of the processing window is proposed.

For the simplicity in the analysis, the bit duration is assumed to be $T_s=1$. Eigenvalues of the received signal covariance matrix are obtained as:

$$\begin{cases}\lambda_k^{\#}=\sigma_n^2(\beta_k(1-\alpha_k)+1) & k=0,1,...,K\text{-}1\\ \lambda_k^{\dagger}=\sigma_n^2(\beta_k\alpha_k+1) & k=0,1,...,K\text{-}1\\ \lambda_k=\sigma_n^2 & k=K,...,M-1\end{cases}, \qquad (4)$$

where M is the dimension of the received signal covariance matrix. According to (4), there are two eigenvalues for each active user in an asynchronous scenario (e.g., $\lambda_k^{\#}$ and $\lambda_k^{\dagger}$), corresponding to these eigenvalues there are two eigenvectors (e.g., $\mathbf{v}_k^{\#}$ and $\mathbf{v}_k^{\dagger}$), each of them contains a part of the spreading sequence of k^{th} user. Maximizing $\lambda_k^{\#}$ by shifting the beginning of the processing window eliminates $\lambda_k^{\dagger}$ and leads to synchronized $\mathbf{v}_k^{\#}$**,** which is called $\mathbf{v}_k^{\text{Sync}}$.

The beginning of the processing window is shifted. $\alpha_k=d_f-\tau_k$, where d_f is the time shift of the beginning of the processing window relative to the beginning of the symbol of 0^{th} user and τ_k is the delay of k^{th} user relative to 0^{th} user. According to the periodic property of α_k's with respect to the beginning of the processing window, $\alpha_k=d_f-\tau_k$ should be substituted with $\text{mod}((d_f-\tau_k),T_s)$ which is the residual of $d_f-\tau_k$ over T_s. By this substitution in (4), the following equation is obtained

$$\begin{cases}\lambda_k^{\#}=\sigma_n^2(\beta_k(1-\text{mod}((d_f-\tau_k),T_s))+1) & k=0,1,...,K\text{-}1\\ \lambda_k^{\dagger}=\sigma_n^2(\beta_k(\text{mod}((d_f-\tau_k),T_s))+1) & k=0,1,...,K\text{-}1\end{cases}, \qquad (5)$$

for any shift of the processing window (e.g., d_f where $\tau_k\le d_f\le\tau_{k+1}$) and for each user (4) shows that, when $\lambda_k^{\#}$ increases $\lambda_k^{\dagger}$ decreases and vice versa. In Equation (5), $\lambda_k^{\#}$ has a maximum at $d_f=\tau_k$ and at this point λ_k^{-1} is minimized. Variation of signal eigenvalues (e.g., $\lambda_k^{\#}$ and $\lambda_k^{\dagger}$) is used for finding synchronization delays relative to the beginning of the processing window. The eigenvalue of the received signal covariance matrix for $k=0,...,K\text{-}1$ is maximized when the beginning of the processing window is matched to that of the symbol. This matching is identified by finding maximum values of the eigenvalues in terms of the processing window shifts, so that is why we call this method as the eigenvalue variation (EV) method. Using the proposed EV based algorithm, the processing window shift, corresponding to the maximized eigenvalue, is the delay of the desired user relative to the beginning of the processing window. In the EV based algorithm, the number of signal eigenvalues should be first determined. This can be done by using the minimum description length (MDL) criterion [14], which is defined as:

$$MDL(k) = -\log\left(\frac{\prod_{i=k+1}^{M}\lambda_i^{1/(M-k)}}{\frac{1}{M-k}\sum_{i=k+1}^{M}\lambda_i}\right) + \frac{1}{2}k(2M-k)\log(L), \quad (6)$$

where L is the number of discrete samples of the received signal $r(t)$, which forms the column vector $\mathbf{r}$. The signal subspace dimension p is estimated as

$$p = \arg_k \min(MDL). \quad (7)$$

The number of the received signal eigenvalues is twice the number of active users in asynchronous scenario (e.g., $2p$). $\lambda_k^{\#}$ and $\lambda_k^{\dagger}$ are calculated in terms of different time shifts from the beginning of the processing window. The number of maximum values of each eigenvalue is K ($2K$ maximum values for both eigenvalues) and each maximum value corresponds to a given delay. So, there are totally $2K$ delays of which K points (delays) are real synchronized delays, which maximize $\lambda_k^{\#}$, while the remaining K points are virtual delays which maximize $\lambda_k^{\dagger}$. For synchronization, virtual delays should be identified and eliminated. By shifting the beginning of the processing window as much as the real synchronized delay for k^{th} user, the number of the eigenvalues of the received signal covariance matrix is reduces by one because the beginning of the processing window is matched to the beginning of the k^{th} user symbol. if two or more users synchronized , the number of signal eigenvalues is reduced more than one. However if the time shift is done by the amount of a virtual synchronization delay, the number of eigenvalues will remain constant. For this reason, eigenvalues of the received signal should be discriminated from the noise eigenvalues, where $k = K,...,M-1$. For discrimination of signal eigenvalues from those of noise, we have proposed the following criterion in

$$\begin{aligned}&\left|\lambda_{normalized}(i+1) - \lambda_{normalized}(i)\right| > \\ &\underset{j=1,\dots M-1}{mean}\left(\left|\lambda_{j+1}-\lambda_j\right|\right) + 8\underset{j=1,\dots M-1}{std}\left(\left|\lambda_{j+1}-\lambda_j\right|\right), \\ &\Rightarrow \lambda_{normalized}(i+1) : signal\end{aligned}$$

(8)

where $\lambda_{normaized}(i)$ is the i^{th} ($i = 1,...,M$) eigenvalue normalized by the largest one and $mean(\cdot)$ is the mean of absolute eigenvalue variations. According to the fact that eigenvalues of noise vary almost continuously, as soon as the difference between two successive normalized eigenvalues is greater than the term $\underset{j=1,\dots M-1}{mean}\left(\left|\lambda_{j+1}-\lambda_j\right|\right) + 8\underset{j=1,\dots M-1}{std}\left(\left|\lambda_{j+1}-\lambda_j\right|\right)$, then $\lambda_{normaized}(i+1)$ indicates the i^{th} signal eigenvalue. Since the arrangement of eigenvalues is in ascending order, eigenvalues with greater indices than i are related to the signal.

IV. Second Phase of The Proposed Algorithm

Using the delays from the proposed EV based algorithm of the previous section for k^{th} user, we are now able to shift the beginning of the processing window to synchronize that user. For the data sequence estimation, the receiver should be synchronized for the desired user. Since the least power user has the worst symbol error rate (SER) among the others, without loss of generality the least power user is considered as the desired user in this paper.

The vector $\mathbf{r}_s$, the received signal vector in which the desired user is synchronized using the EV based algorithm, has the autocorrelation matrix $\mathbf{R}_s$

$$\begin{aligned}\mathbf{R}_s = E\left\{\mathbf{r}_s\mathbf{r}_s^{\,T}\right\} = \mathbf{v}_m\mathbf{v}_m^{\,*} + \sigma_n^2\{\sum_{\substack{k=1\\k\neq m}}^{K-1}\beta_k\{(1-\alpha_k)\mathbf{v}_k^{\#}(\mathbf{v}_k^{\#})^{*} \\ +\alpha_k\mathbf{v}_k^{\dagger}(\mathbf{v}_k^{\dagger})^{*}\} + \mathbf{I}\}\end{aligned}. \quad (9)$$

By performing eigen-decomposition of the matrix $\mathbf{R_s}$, we will get

$$\mathbf{R}_s = \mathbf{V\Lambda V}^T = [\mathbf{V}_s\ \mathbf{V}_n]\begin{bmatrix}\mathbf{\Lambda}_s & 0\\ 0 & \mathbf{\Lambda}_n\end{bmatrix}\begin{bmatrix}\mathbf{V}_s^T\\ \mathbf{V}_n^T\end{bmatrix}, \quad (10)$$

where $\mathbf{V} = [\mathbf{V}_s\ \mathbf{V}_n]$ and $\mathbf{\Lambda} = diag(\mathbf{\Lambda}_s, \mathbf{\Lambda}_n)$. $\mathbf{\Lambda}_s = diag(\lambda_1,\ldots,\lambda_{2K-1})$ contains the $2K-1$ largest eigenvalues of $\mathbf{R}_s$ in descending order and $\mathbf{V} = [\mathbf{v}_1,\ldots,\mathbf{v}_{2K-1}]$ contains the corresponding eigenvectors. When using eigenvectors to blindly estimate the spreading sequences, there will always be 180 degree ambiguity in the estimated sequences. This leads to the ambiguity in the sign of the each chip amplitude in the estimated spreading sequences. In simulations, this amplitude ambiguity is handled by assuming the true spreading sequences have unit amplitudes, and hence normalizing the amplitudes of the estimated chips of the spreading sequences to 1. All users except the desired user (which is synchronized) are asynchronous relative to the beginning of the processing window so each of them produces two eigenvalues. In equation (10), $\mathbf{\Lambda}_n$ is $\mathbf{\Lambda}_n = \sigma_n^2\mathbf{I}_{M-2K+1}$ and $\mathbf{V}_n = [\mathbf{v}_{2K},\ldots,\mathbf{v}_M]$ contains the M-$2K$+1 eigenvectors that correspond to the eigenvalue σ_n^2. We can now whiten the received signal $\mathbf{r}_s$ by using a principle component analysis (PCA) algorithm as:

$$\tilde{\mathbf{r}}_s = \mathbf{\Lambda}_s^{-1/2}\mathbf{V}_s^T\mathbf{r}_s, \quad (11)$$

where $\tilde{\mathbf{r}}_s$ is the whitened data vector. It is proposed to use $\mathbf{V}_s$ instead of $\mathbf{V}$ for data whitening, because the remaining M-$2K$+1 eigenvectors correspond to the noise and cause degradation in the system performance when the system is not working at its full capacity. We can now iteratively update the $(2K-1)\times(2K-1)$ separating matrix $\mathbf{W}$ by utilizing the Hebbian learning rule [15]

$$\begin{aligned}\mathbf{W}(t+1) &= \mathbf{W}(t) + \mu \tilde{\mathbf{r}}_s(t) f(\tilde{\mathbf{r}}_s(t)^T \mathbf{W}(t)) \\ &+ \xi \mathbf{W}(t)(\mathbf{I} - \mathbf{W}(t)^T \mathbf{W}(t))\end{aligned}, \tag{12}$$

in the above equation ξ is a constant (in this paper $\xi = 0.5$); μ is the learning rate; f is a nonlinear function; It is considered that $f(y) = \tanh(ay)$, which is a general purpose nonlinearity and has been shown to work well with almost all types of sources [15]; a is a constant and it is taken as $a = 2$. The user data can now be estimated as

$$\hat{\mathbf{b}} = \mathbf{W}^T \tilde{\mathbf{r}}_s . \tag{13}$$

The signature code matrix $\hat{\mathbf{S}}$ of the users can now be estimated by multiplying the steady state matrix $\mathbf{W}$ from (12) by the dewhitening matrix [16], hence

$$\hat{\mathbf{S}} = \mathbf{V}_s \mathbf{\Lambda}_s^{1/2} \mathbf{W} . \tag{14}$$

The covariance matrix of the estimated users data $\hat{\mathbf{b}}$ is:

$$\hat{\mathbf{R}}_{\mathbf{b}} = E\left\{\hat{\mathbf{b}}\hat{\mathbf{b}}^{\mathrm{T}}\right\}. \tag{15}$$

By eigen-decomposition of $\hat{\mathbf{R}}_{\mathbf{b}}$ and finding $\max\{\lambda_k^{\#}\}$ which is given from the proposed EV based algorithm among the covariance matrix eigenvalues, we are able to find the index of the k^{th} user (e.g., the desired synchronized user) in $\hat{\mathbf{b}}$. It is worth mentioning that all users except the desired one are asynchronous.

V. Simulation Results

In this section, the performances of the two phase proposed algorithm is evaluated in the asynchronous CDMA system through computer simulations. In simulations, the spreading sequences of the users is random BPSK with processing gain of 18dB (N = 63). For each user data BPSK modulation is considered. Chip time and sampling frequency are $50\, n\sec$, and $F_s = 200\, MHz$, respectively. The length of the processing window is assumed 1000 symbols with the duration of 1.575 $m\sec$ and the bit duration of 1.575 $\mu\sec$. Although for synchronization the processing window length of 200 symbols is enough, for sequence estimation the number of symbols in each window should be increased to 1000 symbols for acceptable performance. The slow flat fading is considered for channel model. According to the maximum tolerable Doppler frequency of less than $1/(10\times 1.575\, m\sec) = 63.5\, Hz$ in conventional wireless systems, the assumption of constant channel coefficients, in one processing window is valid.

Simulations are performed with 6 active users; all of them are asynchronous relative to the beginning of the processing window. Users power are 0, 3, 6, 8, 8.5 and 10 dB. Delays of them relative to the beginning of the processing window are 0.2 $\mu\sec$, 0.4 $\mu\sec$, 0.6 $\mu\sec$, 0.8 $\mu\sec$, 1 $\mu\sec$, 1.2 $\mu\sec$ and 1.4 $\mu\sec$, respectively. The number of eigenvalues is estimated using the MDL in (6), which is twice that of the active users in asynchronous scenario. The maximum eigenvalues behavior (MEVB) criterion proposed by [10] is plotted for an equal power and noise free scenario in terms of symbol at Fig. 1-a, it is obvious it can estimate delay of users, but Fig. 2-a shows for aforementioned unequal power scenario,the MEVB can not estimate delay of users with smaller power even in noise free scenario.

Eigenvalues of the received signal (e.g., $\lambda_1,...,\lambda_{11}$ and λ_{12}), in terms of the processing window shifts relative to the beginning of symbol are plotted in Fig. 2. According to the proposed EV based algorithm, the shift value of the beginning of the processing window which maximizes $\lambda_k^{\#}$ corresponds to the delay of the k^{th} user. In this way it is possible to estimate the delay of the desired user in order to synchronize that user. As revealed from Fig. 2, for each eigenvalue there is a maximum peak in terms of the processing window shifts. Root mean square error of delay estimate in chip for EV based estimate is less than 0.05 T_c where SNR of the despread signal is equal to -8 dB for the weakest signal.

Table 1 shows the maximum values of $\lambda_1,...,\lambda_{11}$ and λ_{12} and their corresponding delays. As it is evident from the second column of Table.1, the estimated delays match to the actual considered delays in the computer simulations. Virtual synchronization delays should now be separated form the real ones by using the defined threshold in (8). Fig.3 (a) shows the eigenvalues of the received signal covariance matrix; the number of signal eigenvalues is estimated 12 using (8). Fig.3 (b) is similar to (a), except that in this figure the processing window has been shifted by the amount of the desired user estimated delay (e.g.,$1.2\mu\sec$ which is the real delay related to the lowest power user) from the EV based algorithm. It is obvious that the signal eigenvalue reduces a number. It is worth mentioning that, when the delay corresponds to the virtual eigenvalue is used; the number of signal eigenvalues will not reduce by using the threshold in (8).

The eigenvalue of the received signal covariance matrix related to the desired user (e.g., the lowest power user) is maximized using the proposed EV based algorithm. The processing window shift corresponds to the maximized eigenvalue is the delay of the desired user relative to the beginning of the processing window. Thus the desired user is synchronized and we are now able to use the maximized eigenvalue to identify spreading sequence of the desired user from the estimated spreading sequence of all active users from (13). Because of 6 asynchronous active users there are 12 signal eigenvalues. After synchronization of the desired

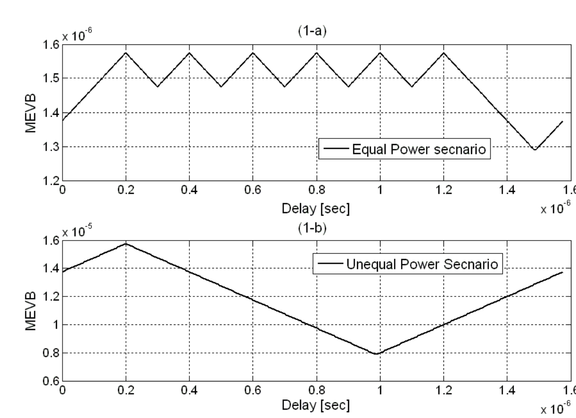

Fig. 1. MEVB for different shifts of the processing window in equal and unequal power scenario.

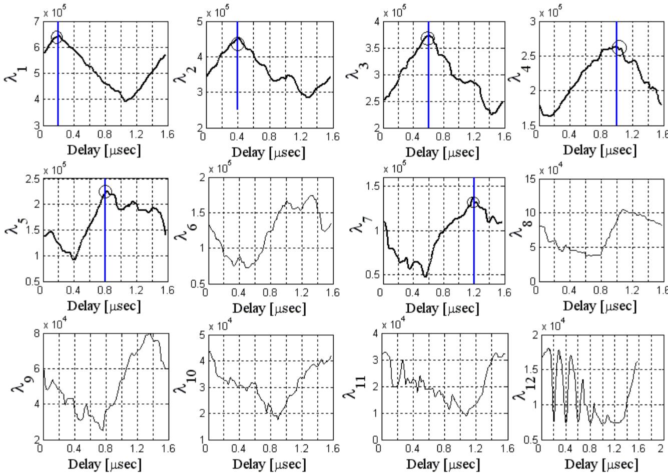

Fig. 2. Eigenvalues behavior for different shifts of the processing window for SNR = -8 dB for weakest signal.

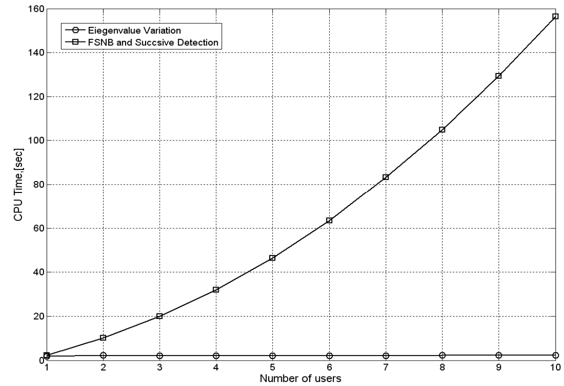

Fig.4. Total used CPU time for simulation of successive detection using FSNB and EV based synchronization methods.

user from the proposed EV based algorithm the number of eigenvalues reduces to 11. Thus 11 eigenvalues and their corresponding eigenvectors are chosen in descending order for whitening.

A computer with CPU AMD Athlone(tm) 64X2 Dual core processor 3600+, 2.01 GHz CPU clock pulse and 1Gbyte RAM has been used for the computer simulations. Fig. 4 shows dedicated time by CPU for simulation of the FROBENIUS square norm behavior (FSNB) with successive detection [11] and the EV based method with estimation of spreading sequence, it is obvious from Fig.4, that increasing the number of users increases the computational complexity of the synchronization method using the FSNB and successive detection. While computational complexity of the EV based method remains constant approximately, and has smaller computational complexity in relative to the FSNB with successive detection for multi user scenario. We have estimated the spreading sequence of each user in the EV based synchronization method for fair comparison between computational complexities of both methods.

Fig. 5 depicts the SER performance in terms of SNR in dB for subspace and ICA algorithms. The results are averaged over 20 Monte Carlo tests with the processing window lengths (PWLs) of 2000 and 1000 symbols. It is evident from this figure that the ICA based algorithm outperforms that of the subspace since it utilizes the high order statistics (HOS) of the received signal. In the ICA algorithm by reduction of the PWL from 2000 symbols with constant step size ($\mu = 0.01$) to 1000 symbols with variable step size ($\mu_1 = 0.1$ for the first 500 iterations and $\mu_2 = 0.001$ for the remaining iterations), the computational complexity is reduced at the cost of little degradation in the SER performance. If the PWL of 1000 symbols with constant step size were used, the ICA method would not have converged. Furthermore increasing PWL by more than 1000 symbols has almost no effect on the SER performance of the subspace algorithm. The effect of over sampling on the SER performance of the detectors is also considered. It is evident that the sampling duration increase from $T_c/5$ to T_c in the ICA algorithm with SER= 10^{-3} needs 2.7dB additional SNR while it has almost no effect in the subspace method SER performance.

In Fig. 6, we have evaluated the achievable steady state signal to interference plus noise ratio (SINR) for the desired

Table 1. Maximum values of $\lambda_1,\ldots,\lambda_{12}$ and their corresponding delays

λ_k	Delay [μsec] real synchronization delays	λ_k	Delay [μsec] virtual synchronization delays
λ_1	0.2	λ_6	1.32
λ_2	0.4	λ_8	1.08
λ_3	0.6	λ_9	1.35
λ_4	0.8	λ_{10}	0.01
λ_5	1.0	λ_{11}	1.45
λ_7	1.2	λ_{12}	1.12

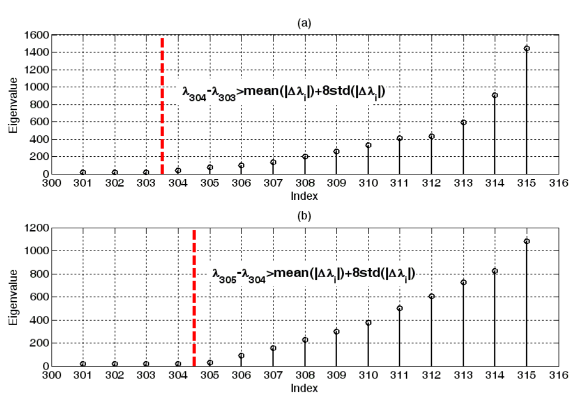

Fig. 3 (a) Eigenvalues of received signal covariance matrix, (b) Eigenvalues of received signal covariance matrix after shifting the processing window by the amount of estimated delay of the desired user

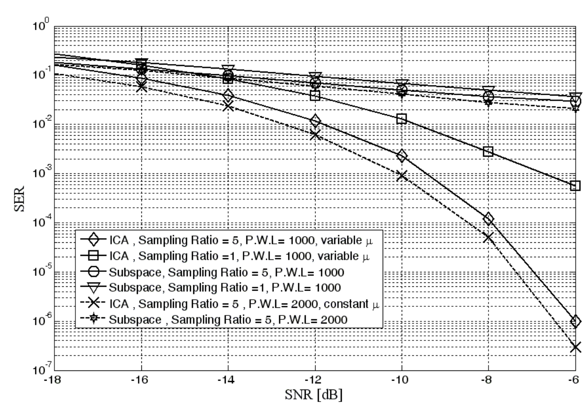

Fig. 5. Comparison of SER for subspace based and ICA based sequence estimation

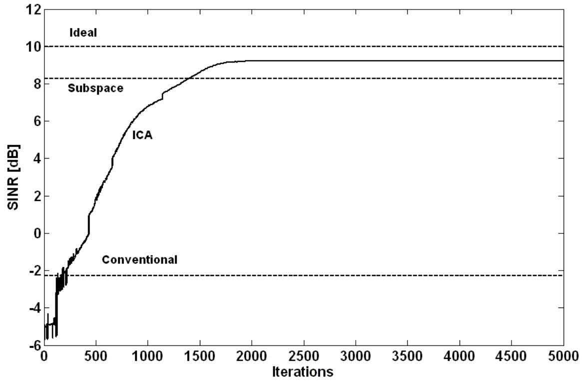

Fig. 6. Comparison of achievable SINR in 10 dB SNR after dispreading

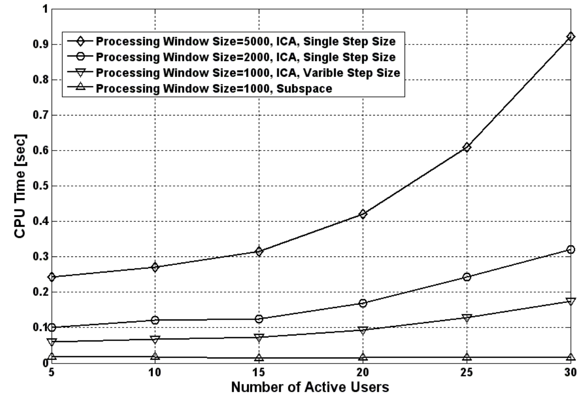

Fig. 7. Dedicated CPU time comparison in terms of number of active users for subspace and ICA algorithms.

user in 10 dB despread SNR. SINR is defined in a CDMA system as in [16]. It is obvious that the ICA algorithm with constant step size converges after 2000 iterations thus the PWL of 1000 symbols with constant step size does not yield convergence. Therefore for the PWL of 1000 symbols variable step size should be used.

Fig.7 shows the dedicated CPU time for different PWLs which represents the computational complexity of the proposed method. Reduction of the PWL from 5000 to 1000 symbols by utilizing variable step size decreases the dedicated CPU time considerably. For example with 6 active users the dedicated CPU time for the PWLs of 1000 and 2000 with almost the same SER performance is reduced 42.2%.

As the slopes of the CPU time curves show, for more active users the dedicated CPU time difference between 1000 and 2000 PWLs increases. According to the fact that the ICA algorithm converges after 2000 iterations, using the PWL of 5000 symbols has a little effect on the SER performance. However it imposes a large computational complexity to the system according to Fig. 6. The only advantage of the subspace algorithm over ICA is that its computational complexity remains almost constant by the growth in the number of active users.

VI. Conclusions

A two phase blind synchronization and data sequence estimation algorithms has been proposed in asynchronous unequal power multi-user DS-SS systems without any prior knowledge about spreading sequences of users in slow flat fading channels. An EV based method is proposed for blind synchronization. Computer simulations confirmed that the proposed algorithm is able to synchronize unequal power signals in SNR = -8 dB for processing gain of 63. A threshold is proposed to identify the real synchronization delays from those (all estimated delays) obtained by the proposed algorithm. For data sequence estimation of the synchronized desired user by the proposed algorithm, an ICA algorithm based on negentropy maximization is proposed. Subspace estimation is used to whiten the received signal as a preprocessing for data estimation. It is shown via computer simulations that using variable step size reduces the computational complexity by more than five times, for 30 active users.

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