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A Social Impact Approach for Digital NBI Mitigation in MC-CDMA Systems

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Abstract

This paper presents a novel social impact approach to detect signals of multi-carrier code division multiple access (MC-CDMA) signals in the presence of narrowband interference (NBI). MC-CDMA is being investigated as an alternative technology for fourth generation (4G) and fifth generation (5G) mobile systems because of its ability to resist multipath fading. Social Impact Theory is based on the socio-psychological behavior of humans in the society. In this paper a social impact based multiuser detector has been employed to mitigate the effect of NBI in MC-CDMA systems. The proposed approach opens a new era of social impact based intelligent networks. The proposed method has been compared with other conventional stochastic methods like Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) on different parameters. Numerical results show that the proposed detector works with much lesser number of iterations and reduces the complexity manifold.

Keywords: Multicarrier Code Division Multiple Access (MC-CDMA), Narrowband Interference (NBI), Multiuser Detection (MUD), Social Impact Theory.

1. INTRODUCTION

MC-CDMA was proposed by Linnartz *et. al*[1] in 1993 . It is a combination of both CDMA and OFDM(orthogonal frequency division multiplexing). MC-CDMA is also termed as CDMA version of OFDM, and because of its ability to combat frequency selective fading and multipath fading it is preferred over OFDM[2-5]. It can be observed that a single symbol is being transmitted on different subcarriers and if any subcarrier fade on the way to receiver even then original symbol can be recovered using diversity combining techniques. We know that CDMA based systems are prone to multiple access interference (MAI) and additive white Gaussian noise (AWGN) and their performance degrades in the presence of MAI and AWGN. MAI occurs due to nonorthogonality of spreading signals. Apart from MAI and AWGN, sometimes short pulses in frequency domain resulting from an unlicensed spectrum interfere with the MC-CDMA signals. These short pulses are termed as narrowband interference signals (NBI)[6]. It may also happen sometimes that an intentional unauthorized person intentionally transmits NBI pulses to jam a MC-CDMA mobile system. Nowadays in urban areas many systems such as UWB (ultra wide band),WLAN(wireless local area network),WIMAX (worldwide interoperability for microwave access), OFDM-LTE (long term evolution) etc. operate simultaneously to provide high data rate. So in such a scenario, it happens sometimes that one system may act narrowband interferer for the other system[7]. NBI signals may also originate from remote controls of various household appliances or cordless phone systems. It has been observed that performance of MC-CDMA systems degrades substantially in the presence of NBI, as NBI may corrupt different subcarriers randomly and at the receiver end we will not be able to reproduce the transmitted signal properly.

Notch filtering has been proved to be an efficient technique to suppress NBI. Notch filter is basically a band-stop filter. A notch filter rejects the frequency band where NBI is present in this way NBI is removed from the spread spectrum signal. In frequency domain NBI mitigation techniques received signal is transformed to frequency domain where each frequency component is compared with already set threshold and frequency components above this threshold are removed. After removal of high energy frequency components, signal is again converted to time domain by using inverse fourier transform[8-11]. Apart from frequency domain method, notch filtering can also be applied in time domain and this method is also termed as estimator/subtractor method. In this method estimated signal is subtracted from the received signal as a result NBI is filtered out[12-16]. Adaptive notch filters like LMS (least mean square) and weighted least M-estimate have also been applied successfully [17-18]. A hybrid technique which involves both frequency domain and time domain NBI suppression techniques was also proposed in [19],

All the methods described above are applied before detection (demodulation) and in all these methods NBI has been modeled as either a sinusoidal signal or an autoregressive process. In both these models, present samples of NBI is correlated with past and future samples i.e. NBI is colored noise. Moreover in all the available methods some kind of extra circuitry (filters etc.) has to be employed prior to the

detector. In practical spread spectrum scenario where MC-CDMA systems are employed to deliver high data rates, it may happen sometimes that NBI which corrupts a MC-CDMA signals can neither be modeled as sinusoidal signal nor as autoregressive process because it is actually a digital interferer signal with random occurrence and it can co-exist as a digital narrowband interference with digital wideband spread spectrum signal. These digital NBI signals are of low data rate in comparison with spread spectrum signal which is of high data rate. So in such a scenario filtration methods described above are not applicable because these filters (linear and non-linear) will not give optimum results when NBI is in the form of a digital signal. For such a problem multiuser detection could be the best solution to mitigate NBI as well as MAI. Verdu in [20] proposed an optimum multiuser detector (OD) which exploits the MAI term to detect different users. This detector works on the principle of maximum likelihood (M-L) detection . A maximum likelihood detector(optimum) has to perform 2^K number of iterations to detect the best possible combinations of bits. So computational complexity is the biggest drawback of optimum M-L detector, and this complexity goes on increasing with increase in number of users. Various sub-optimal detectors based on different stochastic optimization techniques have been proposed by different researchers [21-24]. These suboptimal detectors perform the detection process with much lesser number of computations as compared to optimum M-L detector but their performance slightly degrades in comparison with optimum detector. In this paper we exploit the social impact of majority group on minority group in a society to mitigate the effect of NBI on the MC-CDMA system [25]. Humans are the most intelligent social creature on the earth and a meta-heuristic model based on human social-psychological behavior would be a great step to optimize the technology for better compatibility with humans. Bio-inspired meta-heuristic methods such as Genetic Algorithm, Particle Swarm Optimization, Ant Colony Optimization, Bat Algorithm, Fire fly Algorithm etc. have been extensively used for search strategies and mathematical optimization. These algorithms are affected by poor exploration, inability to achieve global minima and tuning of a large number of control parameters. Moreover optimization techniques involving humans have not been explored yet for solving complex problems in wireless communication. To the best of the literature available, this method has not been employed with wireless communication earlier. Moreover there is no specific method developed to address digital NBI problem in spread spectrum systems so far. In this paper dynamic social impact theory optimization (dSITO) has been applied with optimum multiuser detector and compared with conventional optimization techniques viz GA and PSO. The simulation results show that proposed algorithm outperforms GA and PSO. This algorithm may be statistically better or worse than other algorithms but importance of this algorithm lies in the fact that with this algorithm we have been able to develop a relation between social sciences and the wireless communication technology. The proposed method is novel in the sense that with this algorithm, social sciences can be made compatible with wireless communication technology which will go a long way to bridge the gap between humans and the communication technology. Nowadays a large scale information (data) flow occurs in social media. This information flow over social media cannot be

analyzed easily. It has been observed that network user's socio-economic and socio-psychological interactions could play a major role in analyzing large information (data) in social networks [26-29]. So big data generated over social media can be modeled to design various intelligent social networks with the help of social impact theory.

Rest of the paper has been organized as follows: Section 2 describes the MC-CDMA Receiver Model. dSITO is presented in Section 3. Section 4 is for simulation and discussion. Finally, conclusion is drawn in section 5.

2. MC-CDMA RECEIVER MODEL

The received signal at the base station on the mth subcarrier is given as:

$$r_m(t) = \sum_{k=1}^{K} A_k h_k^{(m)}(t-\tau_k) b_k + n_{wg}(t) + n_{nb}(t) \tag{1}$$

Where,

A_k is the kth user's amplitude, h_k is the kth user's spreading code, b_k is the kth user's transmitted bit, $n_{wg}(t)$ is additive white Gaussian noise (AWGN), $n_{nb}(t)$ is narrowband interference(NBI) modeled as white Gaussian noise. Both NBI and AWGN can be added as both are white Gaussian noise

$$n(t) = n_{wg}(t) + n_{nb}(t)$$

where $n(t)$ is sum of NBI and AWGN Equation (1) can further be written as

$$r_m(t) = \sum_{k=1}^{K} A_k h_k^{(m)}(t-\tau_k) b_k + n(t)$$

Composite signal $r_m(t)$ is correlated with the respective spreading sequence of each user (user 1 to K) at each matched filter. Here auto correlation and cross correlation operations are performed to select desired user's waveform. So outputs of different matched filters for K number of users on m^{th} subcarrier is given in matrix form as:

$$\boldsymbol{Z_m = X_m A b + n} \tag{2}$$

Where $\boldsymbol{X_m}$ is the matrix for the cross correlation (non-diagonal) and auto correlation (diagonal) values of K users detected signals.

$$\boldsymbol{X_m} = \begin{bmatrix} 1 & \rho_{12}^m & . & . & . & \rho_{1k}^m \\ \rho_{21}^m & 1 & . & . & . & \rho_{2k}^m \\ . & . & . & . & . & . \\ . & . & . & . & . & . \\ . & . & . & . & . & . \\ \rho_{K1}^m & \rho_{K2}^m & . & . & . & 1 \end{bmatrix} \qquad \boldsymbol{A} = diag\left[A_1, ..., A_K\right], \ \boldsymbol{b} = \left[b_1, ..., b_K\right]^T,$$

$$\boldsymbol{n} = \left[n_1, ..., n_K\right]^T$$

A represents amplitude matrix of selected signals (waveforms) at different matched filters by autocorrelation operation, ***b*** represents transpose of transmitted bit matrix, ***n*** represents transpose of noise (AWGN) samples.

In matrix $\boldsymbol{X_m}$ above cross correlation (non-diagonal) values are responsible for the occurrence of MAI. In an ideal case values of cross-correlation is zero if waveforms are perfectly orthogonal, but in a wireless environment orthogonality of waveforms cannot be maintained. For this very reason multiuser detection has been employed which results in better BER performance and increased system capacity as far as MC-CDMA system is concerned.

The bit vector $\hat{b}$ which will minimize the error between matched filters outputs $\boldsymbol{Z_m}$ and the estimated values will be determined by the following equation (4) for the optimum multiuser detector (M-L detector).

$$\hat{b} = \arg\min_{b} \left|\boldsymbol{Z_m} - \boldsymbol{AX_m b}\right|^2 \tag{3}$$

This method searches all possible bit vectors to determine the one that minimizes the square error between matched filters outputs $\boldsymbol{Z_m}$ and the estimated values. So we have to choose $\hat{b}$ such that estimated signal is closest to the received signal. The optimum estimate of $\hat{b}$ will minimize the probability of error. The equation (3) above can be further written as:

$$\hat{b} = \arg\left\{\max_{b\in\{-1,1\}^K} [2\boldsymbol{b^T AZ_m} - \boldsymbol{b^T AR_m Ab}]\right\} \tag{4}$$

Hence, for K users MC-CDMA system, a MUD chooses a bit vector $[b]_{K\times 1}$ which will maximize the objective function of equation (4) according to maximum likelihood criterion (M-L detection).

3. DYNAMIC SOCIAL IMPACT THEORY

Social impact theory is inspired by social behavior of human beings. Social impact theory (SIT) was created by Bibb latane [36] in 1981.The basis of this theory is how people in a society affect one another in different social situations. Different types of

emotions such as anger, humor, embarrassment etc. affect every member in a society. This theory pushes individual members of a society to think in a particular way. Opinions or attitudes of people in a society can be changed by persuasion. This socio-psychological theory of human social interactions can be translated into following three equations.

1. **First law:** This law deals with the social impact on any individual in a society. The equation of social impact $I= f(SIN)$ illustrates that there is more social impact when number of sources (number of people (N)) in a society is more and their action is more immediate (I) and they strike the target with more strength(S). Immediacy represents the closeness of sources (N) in space or time.
2. **Second law:** This law is psychosocial law. It states that addition in a small group is more significant and takes more attention than addition in a large group. Equation $I = sN^t$ describes the second law of SIT where t is power of N (number of people) and s is any constant which represents social impact.
3. **Third law:** The third rule of social impact is multiplication/division of impact. It states that social impact, strength and immediacy will get divided if number of targets (number of individuals (N)) in society increases. This law is given by the equation $I = f(1/SIN)$.

In 1990 Novak *et al.* [30] gave dynamic social impact theory which was a slight modification of earlier simple social impact theory. In this theory Novak *et al.* emphasize that if any individual exert social influence on other individual it also gets affected by the same amount of social influence i.e. in this theory some kind of dynamicity is added.

The dynamic Social Impact Theory based optimizer (dSITO) can now be implemented [31-32]. dSITO is binary optimization method which is based on socio-psychological theory of humans in a society. The dSITO algorithm holds a spatially distributed population (number of sources/individuals in a society) in a 3-dimentional array. Now fitness (strength) of each individual is assessed by going through a large number of iterations. Each individual in dSITO tries to influence other individuals according to its own strength. Moreover dSITO emphasizes that individuals in a society continue to interact with each other, as a result their view or opinions are changing constantly, but at some point of time all their actions or opinions becomes uniform. This point may be termed as the point where population convergence starts and iterations end.

3.1 dSITO terminology

In this section social impact theory [25] has been made compatible with wireless communication. We know that in wireless communication signals are transmitted and received in the form of bits (digital signal) so society of a wireless communication

system can be termed as a group of bits in a two dimensional (*2-D*) lattice. Various terms used in this algorithm are as follows:

Society size: Society size is the number of different user's transmitted bits e.g. a 4×4 society size contains 16 bits in square topology with four rows and four columns. It is a society of 16 bits transmitted by 16 users.

Attitude: It is the status (either 0 or 1) of each bit of each user. It may change after each iteration. It can also be termed as initial population. In a communication system bits transmitted may have either a 0 status or a 1 status and on the way from transmitter to receiver status of a bit may change due to MAI and some other types of interferences.

Diversity factor (*D*): It is the probability with which an individual bit may change its attitude. It represents the probability of spontaneous change. The value may range between [0:1].

Self-Confidence Distance parameter (δ): This parameter represents the relative importance of an attitude with itself. A higher value of δ represents a low self confidence attitude level. It is generally taken as equal to 1.

Society fitness: Maximum fitness, minimum fitness and average (mean) fitness value of society can be calculated using objective function (fitness function) specified in equation (4).

Society strength:

$$(Sn) = \frac{f_{\max} - f_{avg}}{f_{\max} - f_{\min}} \tag{5}$$

Where f_{max} and f_{min} are maximum and minimum fitness values of society (population) and f_{avg} is the average fitness value of the society. Maximum society strength is taken as 1.

Neighborhood: In social impact theory neighborhood plays a major role. An individual bit in a society is affected by its immediate neighborhood bit. Value of neighborhood distance (radius) (d_i) affects the process of optimization.

Social Impact: Individual bits are assumed to affect each other's attitude. The total impact I is the difference between persuasive impact (I_p) of those individual bits that holds the opposite view (opposers) and supportive impact (I_s) of those individual bits that hold the same view (supporters).

$$I_p = N_o^{1/2} \left\lfloor \sum \left(P_i / d_i^2 \right) / N_o \right\rfloor \tag{6}$$

$$I_s = N_s^{1/2} \left\lfloor \sum \left(S_i / d_i^2 \right) / N_s \right\rfloor \tag{7}$$

where, P_i is the persuasiveness of individual bit i, S_i is the supportiveness of individual bit i, N_o is the number of sources (individuals with an opposing view), N_s is

the number of individuals sharing the individual's view and d_i is the euclidean distance (radius) between the individual bit and its neighborhood bit.

3.2 Flow-Chart of dSITO

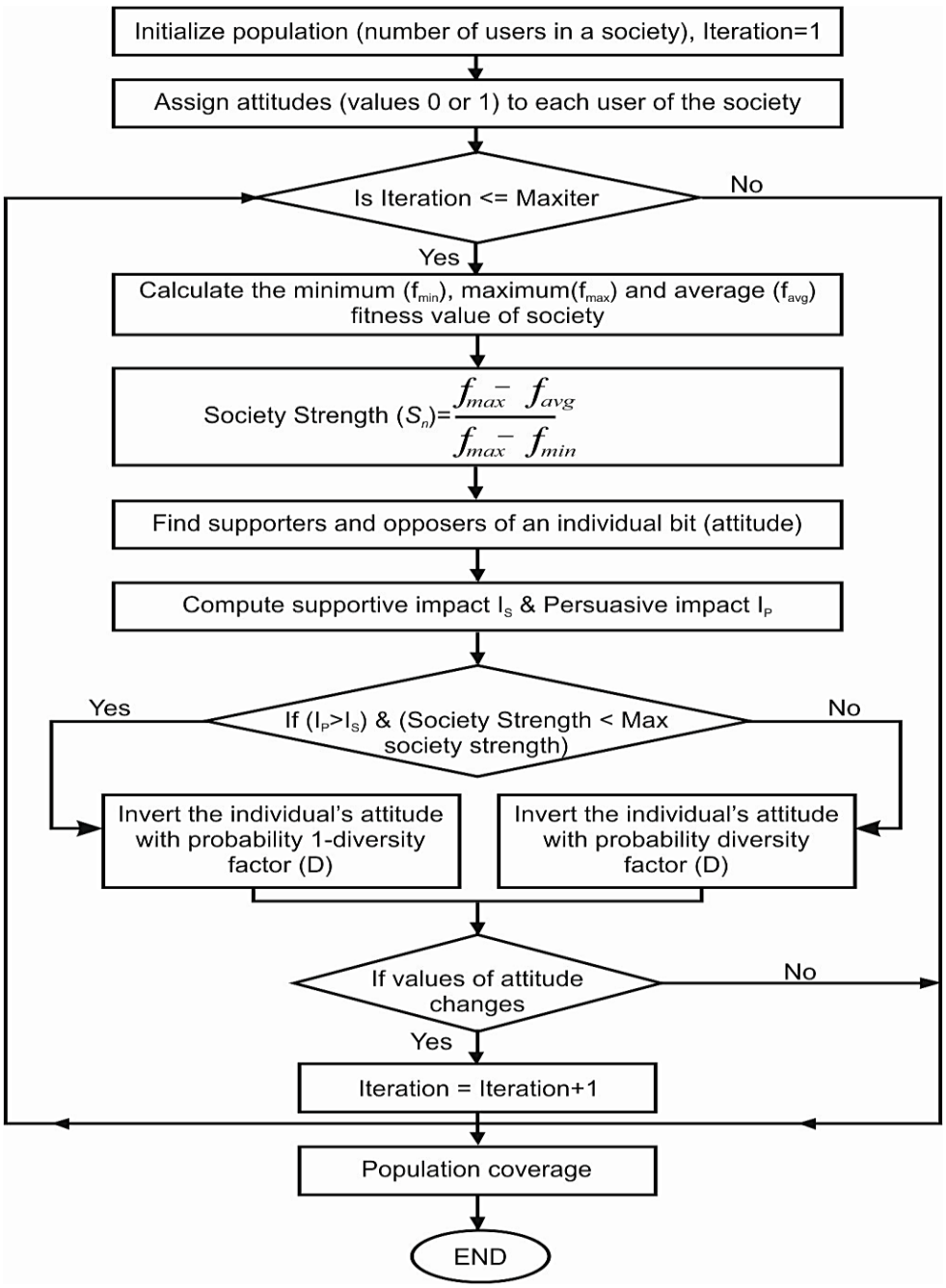

Figure 1: Flow-chart of dSITO

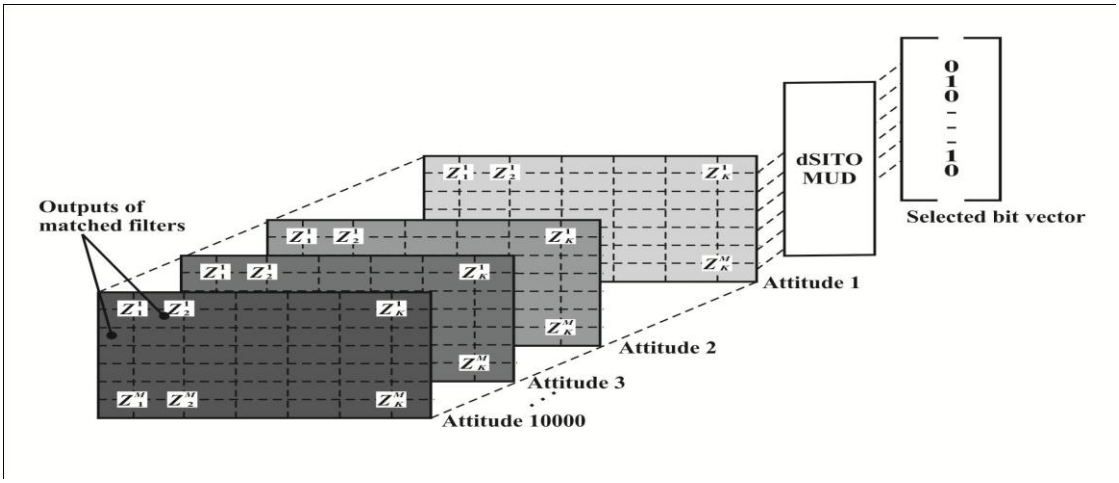

Figure 2: dSITO implementation with multiuser detector

As shown in Figure 2, different transmitted bits (attitudes) are received by dSITO based MUD. These bits (matched filters outputs) are interacted with their neighbor bits in the form of 2-dimensional (*2-D*) lattices. Since each user transmits a total of 10000 bits so a total of 10000 attitudes (*2-D* lattices) are processed by dSITO based MUD.

4. SIMULATIONS

In this problem an asynchronous (uplink) MC-CDMA system is considered. Gold code of length 31 is used as spreading sequence. Here it is assumed that narrowband interferer signals are of Gaussian in nature and it is assumed that these NBI signal affect different subcarriers randomly with variable intensity (Interference Power).Perfect subcarrier synchronization with no frequency offset is assumed. Each subcarrier will go for independent fading as channel is asynchronous (uplink).It is also assumed that there is no non-linear distortion of any kind. Channel is AWGN and modulation used is QPSK (quadrature phase shift keying).

4.1 Convergence of dSITO

Convergence properties of Social Impact Theory have been analyzed extensively in [30-32]. Convergence properties of dSITO have been analyzed using objective function in (4) along with GA and PSO. Various parameters of GA, PSO and dSITO have been synchronized for a fair comparison. Different combinations for different values of these parameters have been tested for 100 runs for this algorithm. Table 1 gives the tuned parameters for all the algorithms.

Table 1: Control parameters of GA, PSO and dSITO

Genetic Algorithm (GA)		**Particle Swarm Optimization (PSO)**		**Dynamic Social Impact Theory Optimization (dSITO)**	
Iterations	100	**Iterations**	100	**Iterations**	100
Selection rate	0.5	**Velocity clamping factor**	2	**Diversity factor (D)**	0.97
Mutation Type	Bit flip	**Cognitive constant**	2	**Maximum society strength**	1
Mutation rate	0.15	**Social constant**	2	**Neighborhood**	Random neighborhood
Crossover Type	Uniform	**Minimum inertia weight**	0.4	—	—
Crossover fraction	0.8	**Maximum inertia weight**	0.9	—	—
Elitism count	2	—	—	—	—

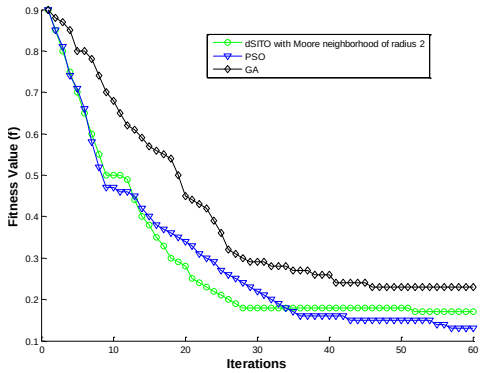

Figure 3: Evolution progress of dSITO (Moore neighborhood of radius 2), GA, PSO

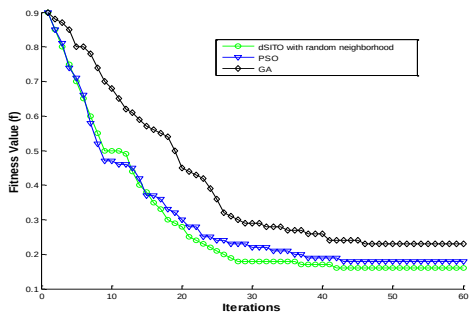

Figure 4: Evolution progress of dSITO (with random neighborhood), GA, PSO

Figure 3 above shows the evolution progress of all the algorithms for average fitness value of the society. It can be observed from the Figure 3 that PSO converges to a lower value than dSITO and GA. This is because of the fact that in PSO individuals are free to interact directly with other individuals but in dSITO, movement of individuals are restricted due to Moore neighborhood of radius 2. GA gives the worst performance because crossover and mutation operation hinders the fitness improvement. In Figure 4 with random neighborhood, dSITO is better than PSO and GA. Reason for such a performance can be attributed to the fact that population of dSITO is scattered in three dimensions (*3-D*) [33] and few control parameters are employed in comparison with GA and PSO as can be seen in Table 1. Like PSO, dSITO also does not perform any selection, crossover and mutation operation as done in GA. In dSITO all individuals in population step into next generation (attitude level) but each individual differ in its strength. Moreover unlike in other evolutionary algorithms where every individual influences other individual and also gets influenced by other individual by the same impact, in dSITO amount of impact is not equal. A strong individual can influence other individual with greater impact or with lesser impact.

4.2 Performance Evaluation

First we will simulate a MC-CDMA system with 5 subscribers to observe the effect of NBI on the MC-CDMA transmitted signals. It is assumed that MC-CDMA signals are not affected by AWGN on the way to receiver (detector).Two narrowband interferer of variable intensity (signal to interference ratio (SIR) of5 dB and 8 dB) are added to the transmitted MC-CDMA signal. Each user transmits 10,000 bits.

Figure 5 shows the power spectral density (PSD) of 1st subcarrier without NBI and Figure 6 shows the PSD of same subcarrier with NBI. It can be easily observed from the Figure 6 that subcarrier is corrupted by the addition of NBI signal. Figure 10 shows the BER performance of MC-CDMA signal with and without NBI. It clearly shows that NBI increases the BER of the received signal. Since we have already observed the effect of NBI signals on MC-CDMA signals. Now MC-CDMA signals are to be detected by our proposed detector received. Here number of subcarriers taken is equal to number of users. This is done to achieve square topology of attitudes in every 2 dimensional (*2-D*) lattice as shown in Figure 2. Here we assume perfect subcarrier synchronization with no frequency offset and there is no nonlinear distortion. QPSK modulation is used in simulation. Simulations of the algorithms have been carried out in MATLAB® using standard libraries for GA (Global optimization tool), for PSO (psomatlab) and dSITO library has been developed in-house.

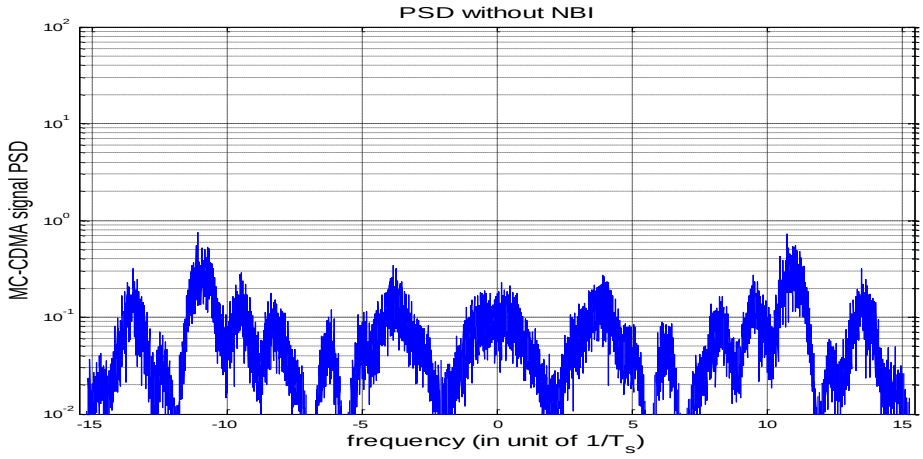

Figure 5: PSD of subcarrier without NBI

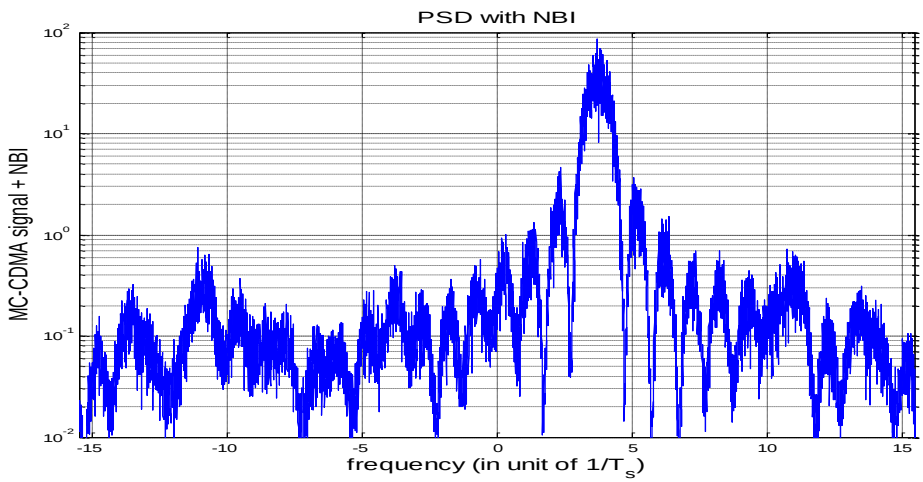

Figure 6: PSD of subcarrier with NBI

4.3 PSD Performance

As shown in Figure 2 outputs of matched filters with their respective attitudes (bits) have been given to the dSITO-MUD in square topology as a two dimensional (*2-D*) lattice. Every *2-D* lattice contains attitude levels (transmitted bits) of matched filters for K number of users where each user is transmitting over *M* subcarriers, but in this case we have taken *K=M*. Suppose a MC-CDMA system consists of 5 users with 5 subcarriers. Each user transmits 10,000 bits. Total population in this case can be represented as 5×5×10000 (*3-D*) where 10000 bits can be termed as the 10000 attitudes in dSITO terminology. Attitude 1 can be represented as a *2-D* lattice of 16 attitudes (bits) in 5×5 square topology. Values of attitude can be either 0 or 1.

Similarly Attitude 2 gives next 25 attitudes. So all the attitudes i.e. from Attitude 1 to Attitude 10000, represent all 10000 bits of each user received by dSITO-MUD. Each *2-D* Attitude lattice is processed by dSITO-MUD with a number of iterations. Supportive impact (I_s) of an individual bit goes on increasing with every iteration and so is the society strength, until a bit vector (25×1) is selected which never changes its attitude. These are the detected 25 bits of 5 users where each user is detected with 5 copies of same bit/symbol to maintain frequency diversity as is the case with MC-CDMA systems. It can also be observed from the Figure 7(a-c-e) that subcarriers are affected by the three NBI signals. It can be observed from the Figure 7(b-d-f) that effect of NBI signals have been mitigated to a large extent after three subcarriers are processed by dSITO based MUD.

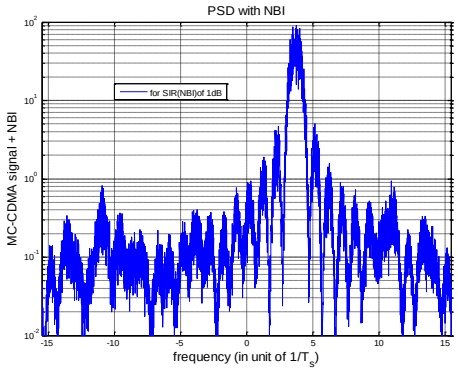

Fig. 7(a)

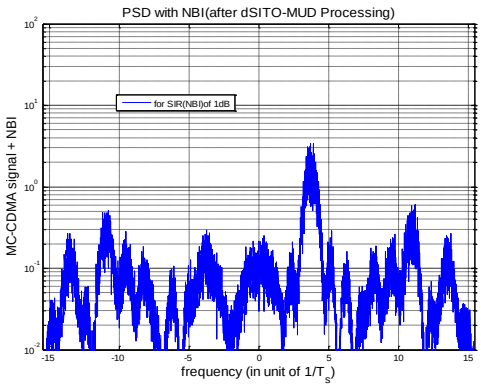

Fig. 7(b)

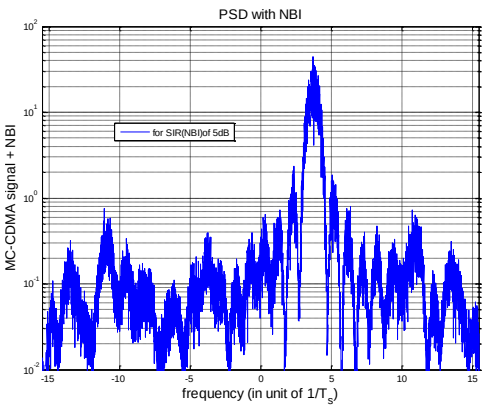

Fig. 7(c)

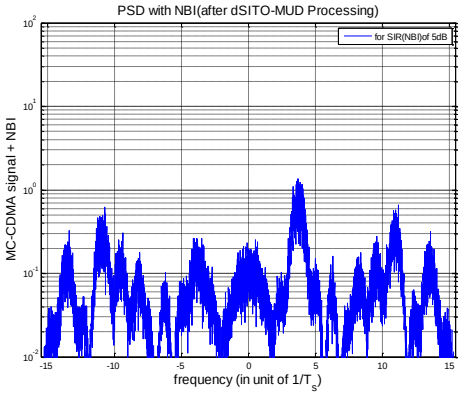

Fig. 7(d)

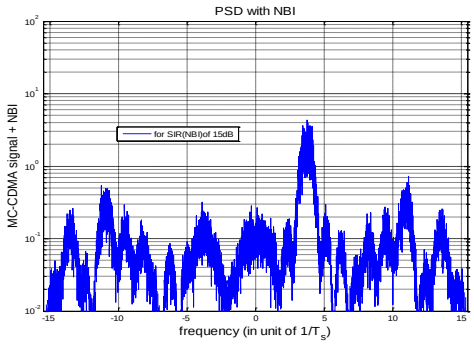

Fig. 7(e)

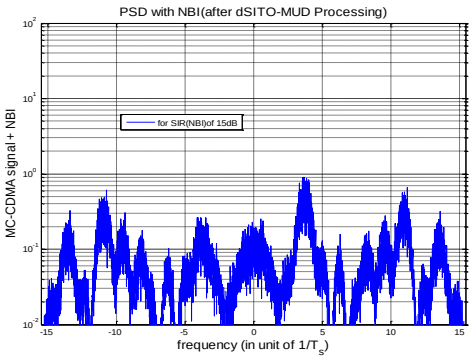

Fig. 7(f)

Figure 7: PSD of subcarriers affected by NBI. (a-c-e) without dSITO-MUD processing, (b-d-f) with dSITO-MUD processing

4.4 BER Performance

Figure 8 below shows the BER (Bit Error Rate) performance of GA based MUD (GA-MUD) , PSO based MUD (PSO-MUD), dSITO-MUD and OD against different values of SNR(Signal to noise ratio) denoted as E_b/N in decibel (dB). It can be observed that dSITO-MUD detector achieves a near optimal performance which is better than GA-MUD and is comparable to PSO-MUD. It means dSITO-MUD gives excellent performance which is at par with optimal detector.

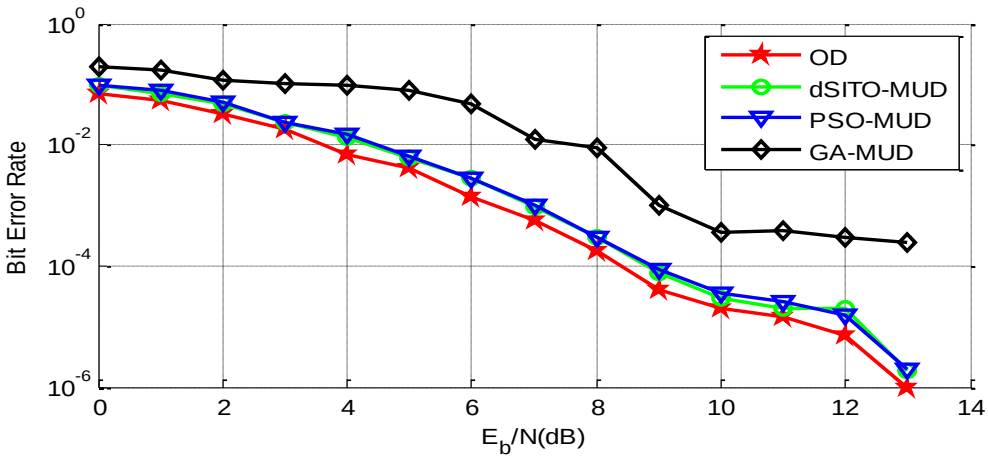

Figure 8 : BER Performance

5. CONCLUSIONS

In this paper dSIT has been exploited to detect and correct NBI affected bits by using multiuser detection. We have tried to develop a relationship between social sciences and wireless communication. This novel work could be a handy tool for developing social influence based intelligent communication networks like Location based social networks (LBSNs). dSIT could also be applied for congestion control in cellular mobile communication, resource allocation in wireless networks etc. Moreover dSIT could play a great role to interface humans with computers and communication networks. Simulation results show that performance of dSITO is better than GA and in equality with PSO. Novelty of this method is that it simultaneously mitigates the effect of NBI, MAI and AWGN without employing extra circuitry before detection. The dSITO algorithm is still in its infancy and has not been explored to its full potential. Moreover there is a need to develop different versions of this algorithm to make it applicable to different applications for optimum results.

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