Research Paper

LARGE SCALE MULTIPLE-INPUT MULTIPLE-OUTPUT (LS-MIMO) DETECTION USING GENETIC CAT SWARM OPTIMIZATION

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ABSTRACT

Large Scale Multiple-Input Multiple-Output (LS-MIMO) is an emerging technology system employs multiple antennas at the transmitter and receiver sides. The receivers used in MIMO-OFDM are complex. Due to reduction in computational Complexity, Computational Intelligence finds its application in the field of MIMO detection. In this paper, a novel hybrid algorithm called Genetic Cat Swarm Optimization (GCSO) is proposed and put upon for the first time in MIMO detection. The new algorithm called GCSO MIMO achieves maximum likelihood performance and proved that the search space is reduced when compared with other optimizing algorithms like GA, CSO.

KEYWORDS: LS-MIMO, GCSO, GA and CSO.

1. INTRODUCTION

In wireless communication, supporting the data and voice, video over the network, symbol detection, carrier assignment in MIMO and network planning are some of the research problems. Optimization techniques are used to reduce the problem complexity. Recent researches in optimization technique say Computational Intelligence (CI) is a powerful tool to solve complex problems and reduces the search space. Since MIMO detection involves in complex problem, here CI is applied to solve the problem effectively by reducing the flop/block in MIMO detection.

The complexity of receiver used in conventional MIMO-OFDM detection is high. To solve this problem, optimum receivers were designed but with strangulated performances. Evolutionary algorithms (EA) like Genetic Algorithm (GA), have been successfully applied in the field of MIMO detection (Fei and Wang 2010). LTE and 4G mobile communication allows upto eight antenna elements at the without increasing the Bandwidth, they can improve the reliability of the link.

A novel signal detector based on QGA for MIMO-OFDM system is proposed [1].It results shows that the proposed detector has more powerful properties in bit error rate than conventional Genetic Algorithm (GA) based detector and Vertical Bell Layered Space Time (VBLAST) algorithm based detector. The performance of the proposed detector is closer to optimal, compared with the other detectors. The results demonstrated the effectiveness and the applicability of QGA in signal detection for MIMO-OFDM system.

Obaidullah et.al [2], compared the performance and complexity and focus instead on the selection of GA parameters, such as population size, P, generation number G, and mutation probability, pm, for the GA in MIMO detection and we employ a meta (or outer) GA to optimize P, G, and pm values for the inner GA employed for MIMO detection. The meta-GA approach helps reveal that the parameters of the inner GA should be tuned in order to achieve maximum performance for the lowest numerical complexity.

Alansi et.al [3], presents the results of implementing multi-user detector (MUD) in SDMAOFDM systems based on an advanced genetic-algorithm (GA) optimization tool. The hardware implementation is performed using Field Programmable Gate array (FPGA) devices which allow the real time performance of the proposed tool. Results show that the GA scheme enhances the performance and provides BER near to that attained using maximum likelihood (ML) detector at considerably lower computation complexity.

Svac et.al [4], in this paper proposed a low-complexity detector for multiple-input multiple-output (MIMO) systems using BPSK or QAM constellations. The detector operates at the bit level and is especially advantageous for large MIMO systems. It consists of three stages performing partial ML detection, generation of soft values, and soft-input genetic optimization. The genetic programming algorithm is used in the last stage, it gives the detector can outperform state-of-the-art methods, and its complexity scales roughly cubically with the system dimension.

The rest of the paper is organised as follows: Section 2 discusses the Large Scale Multiple-Input and Multiple-Output. Genetic Algorithm (GA) is discussed in section 3A and the Cat Swarm Optimization (CSO) is discussed in section 3B. The Proposed Genetic Cat Swarm Optimization (GCSO) is discussed in section 4. In section 5 the results were analysed .Finally Section 6 concludes our research and future work is discussed.

I. LARGE SCALE MULTIPLE-INPUT AND MULTIPLE-OUTPUT

The emerging massive/large-scale multiple-input multiple-output (LS-MIMO) systems that rely on very large antenna arrays have become a hot topic of wireless communications. Compared to multi-antenna aided systems being built at the time of writing, such as the long-term evolution (LTE) based fourth generation (4G) mobile communication system which allows for up to eight antenna elements at the base station (BS), the LSMIMO system entails an unprecedented number of antennas, say 100 or more, at the BS. The huge leap in the number of BS antennas opens the door to a new research field in communication theory, propagation and electronics, where random matrix theory begins to play a dominant role.

Interestingly, LS-MIMOs also constitute a perfect example of one of the key philosophical principles of the Hegelian Dialectics, namely that quantitative change leads to qualitative change. In this treatise, we provide a recital on the historic heritages and novel Challenges facing LS-MIMOs from a detection perspective. Firstly, we highlight the fundamentals of MIMO detection, including the nature of co-channel interference (CCI), the generality of the MIMO detection problem, the received signal models of both linear memoryless MIMO channels and dispersive MIMO channels exhibiting memory, as well as the complex valued versus real-valued MIMO system models. Then, an extensive review of the representative MIMO detection methods conceived during the past fifty years (1965-2015) is presented, and relevant insights as well as lessons are inferred for the sake of designing complexity-scalable MIMO detection algorithms that are potentially applicable to LS-MIMO systems.

Furthermore, we divide the LS-MIMO systems into two types, and elaborate on the distinct detection strategies suitable for each of them. The type-I LS-MIMO corresponds to the case where the number of active users is much smaller than the number of BS antennas, which is currently the main stream definition of LS-MIMO. The type-II LS-MIMO corresponds to the case where the number of active users is comparable to the number of BS antennas. Finally, we discuss the applicability of existing MIMO detection algorithms in LS-MIMO systems, and review some of the recent advances in LS-MIMO detection.

II. GENETIC ALGORITHM CAT SWARM OPTIMIZATION

A. Genetic Algorithm

GA is an optimization technique used to solve problems that mimic biological evolution. GA often provides effective search mechanisms that can be used in classification applications.

Genetic Algorithms (GA) was invented by John Holland in 1970s at Michigan University. The main goal was to design an algorithm in order to solve certain complex problems and to study the adaptation phenomenon which occurs in nature.

GA is an optimization technique that reflects in a primitive way some of the process of genetics and natural evolution. GA is used to solve problems that mimic biological evolution. GA often provides effective search mechanisms that can be used in classification applications. Random search methods work effectively within certain boundaries or under specific limiting conditions only. Whereas GAs are highly efficient and there is no limitation or restrictions in the search space. Moreover, in random search methods, the algorithm may get baffled into the problem of local minima which increases the computational time.

In order to solve a complex problem, the problem must be represented as a genome and genomes must form a set of elements encoded into bit-strings called chromosomes (Randy and Sue 2004). A significant parameter called the fitness function, allows the each chromosome to be evaluated quantitatively. GA starts with a set of chromosomes named as generation. Chromosomes from one generation are taken and used to form a new generation by considering that the new generation will have better solutions than the older one. According to the fitness value evaluated for each chromosome, selected chromosomes forms new solutions called as offspring. The most suitable chromosome has more chances to survive in the next generation. Table I compares how GA parameters are used in MIMO detection.

A simple GA that yields good results is composed by three operators: Reproduction (Selection), Crossover and Mutation. First, the Selection process is used to take the chromosome from current population to form new solutions. The success rate of GA depends on the parameters used in crossover and mutation operation.

The selected transmit vectors called parent vectors will mate with one another to produce children vectors (offspring), where the children consist of genetic material from the two parents. Some of the parent signal constellation may be used in the new generation based on the fitness value. The various selection strategies are Population Decimation, Proportionate Selection and Tournament Selection (Melanie 1998).

TABLE I: COMPARISON BETWEEN GA AND GA IN MIMO

Parameter	GA	GA in MIMO Detection
Gene	A single bit in chromosome	Four bit/symbol
Chromosome	Any Possible Solution	Any Possible received symbol
Population	Group of Chromosomes	Group of received Symbols
Cost Function	A Function to evaluate the performance metrics	Symbol detection Euclidean Distance
Generations	Number of generation	Number of Iterations

a) Reproduction

Reproduction process is used to select the chromosome (transmitted symbol/ signal constellation) from current population to form new set of vectors that minimizes the error. The selection technique is related to the fitness value of each signal constellation in the population. A selection strategy determines which chromosome surveys in the next generation.

The selected transmit vectors called parent vectors will mate with one another to produce children vectors (offspring), where the children consist of genetic material from the two parents. Some of the parent signal constellation may be used in the new generation based on the fitness value.

The various selection strategies are Population Decimation, Proportionate Selection and Tournament Selection (Melanie 1998). In Population decimation, the signal constellations are sorted according to the cost (expected symbols). Once they are sorted, then selection process is based on the ranking allotted to each chromosomes. In Proportionate Selection, the signal constellation is selected based on its fitness value and the fitness of the total population. This type of selection technique is also called as Roulette-wheel Selection (RWS) technique. The signal constellations with higher fitness i.e. minimum, have higher probability for selection. In case of Tournament Selection, two signal constellations are randomly selected and signal constellation with higher fitness is selected. This process is continued until the required numbers of offspring are generated.

b) Mating

After Selection, mating is performed. While Selection addresses the issue of selecting which vectors will take part in the evolution process, mating selects which two parent chromosomes will mate with one another. Several Mating schemes are possible.

The mating schemes are Adjacent Fitness pairing (AFP), Emperor Selective mating (ESM) and Best Mates-Worst (BMW). In case of AFP, the two signal constellation with the lowest fitness mate together, the chromosomes with the next two lowest finesses mate together, and so on. In ESM, the highest ranked individual mates with the second highest, fourth highest, etc. individuals (that is, with all even order individuals), while the third; fifth, etc. individuals (that is, those with odd order) remain unchanged. In BMW mating scheme, the signal constellation with the highest fitness is mated with the chromosome of lowest fitness, the second best mates with second worst and this process continues until the required population size is obtained. The figure 1 shows the different mating schemes used in GA.

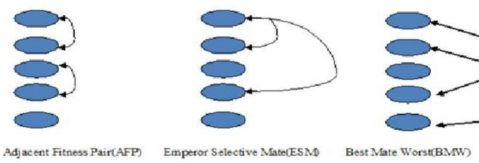


Fig.1. Mating Schemes in GA

c)Crossover

The next operation performed by GA is crossover, which selects genes from parent chromosomes and creates a new offspring (Collin and Rowe 2003). Once the children signal constellations are selected the next process carried out is crossover. The cleft point is determined by the crossover point, which takes the value between 0 and signal constellation length.

This process is explained using a simple example by considering a 32bit which represent 8 different symbols. Consider the following two parent keys:

Parent signal constellation #1:011101010100110100100011 (754D23)

Parent signal constellation #2:100111011101101011111110 (9DDAFE)

Crossover mates the two parent constellation to produce two offspring (children constellation).

Parent signal constellation #1: 011101 010100110100100011 (754D23)

Parent signal constellation#2: 100111— 011101101011111110 (9DDAFE)

Children Signal constellation #1: 011101011101101011111110 (75DAFE)

ChildrenSignalconstellation#2:100111010100110100 100011 (9D4D23)

The crossover rate should be selected properly else too low crossover value may stagnate the algorithm or too high crossover value may eliminate the good chromosome. The performance of GA can be improved from the no crossover to optimum crossover. The crossover operation improves the convergence more apace. From the analysis, crossover is used for combining the multiple schemata into one string.

d)Mutation

The mating process is continued by mutation, which randomly changes one or more bits in the chromosome. The mutation operator randomly changes one or more bits in a vector, thus preventing the population from missing the optimal fitness value. As an example shown below, the tenth bit equal to 1 is mutated to a 0 to obtain a new key.

Before mutation: 1001110111011110 11110000(9DDEF0)

After mutation: 10011101100111101111 0000(9D9EF0)

This process continues until a suitable optimum solution is found, or certain number of generations has passed.

B. Cat Swarm Optimization

The tracing mode of CSO has two equations: velocity update equation and position update equation. For reaching to an adaptive CSO, we change some of the parameters in velocity equation. Also for computing the current position of cats, we consider the information of previous and next dimensions by using a special factor and then we achieve a new dynamic position update equation. We describe the proposed algorithm in two parts.

a) Using Adaptive Parameters

In the proposed algorithm, we add an adaptive inertia weight to the velocity equation which is updated in each dimension. By using this parameter, we make a balance between global and local search ability. A large inertia weight facilitates a global search while a small inertia weigh facilitates a local search. First we use a large value and it will be reduced gradually to the least value by using (1).

$$W(i) = W_s + \frac{i_{\max} - i}{2 \times i_{\max}} \tag{1}$$

Equation (1) indicates that the inertia weight will be updated adaptively, where Ws is the starting weight, i_{max} is the maximum dimension of benchmark and i is the current dimension. So the maximum inertia weight happens in the first dimension of the each iteration and it will be updated decreasingly in every dimension. In the proposed algorithm Ws is equal to 0.6. Also, c1 is an acceleration coefficient for extending the velocity of the cat to move in the solution space. This parameter is a constant value and is usually equal to 2.05, but we use an adaptive formula to update it by (2).

$$C(i) = C_s - \frac{(i_{\max} - i)}{2 \times i_{\max}} \tag{2}$$

Equation (2) demonstrates that the adaptive acceleration coefficient will be gradually increased in every dimension and the maximum value happens in the last dimension. Here Cs is equal to 2.05. By using these two adaptive parameters, we change the velocity update equation for each cat to a new form describing in (3).

$$V_{k,d} = W(d) + V_{k,d} + r_1 \times C(d) \times (X_{best,d} - X_{k,d}) \tag{3}$$

b) New Dynamic Position Update Equation

In this part, we change the position update equation to a new form. In the pure CSO, the position of cat is including of current information of velocity and position. Sometimes in many cases, using of previous information in order to estimate the current position is useful. Also, taking the advantages of next information can be appropriate information for updating the cat's position. So we use the two previous/next dimensions information of velocity and position by applying a new factor which is called Forgetting factor. By this factor, the values of previous and next steps will be different. So the information value for first previous/next step is higher than second previous/next step. It means that the influence of previous/next step is more important than previous/next second step. New position update equation is described by (4).

$$X_{k,d} = \frac{1}{2}[(Position\,Information) + (Velocity\,Information)] \quad (4)$$

$$Position\,Information = \quad (5)$$

$$V_{k,d} + \frac{\gamma \times (X_{k,d+1}) + (1-\gamma) \times (X_{k,d+2})}{2} + \frac{\gamma \times (X_{k,d-1}) + (1-\gamma) \times (X_{k,d-2})}{2}$$

In the proposed algorithm, is the forgetting factor and is equal to 0.6 (It is necessary to use Y > 0:5). This new position update equation is composing two new dynamic terms, average position information and average velocity information. Here, we use the current and the average information of first and second previous/next dimensions for both velocity and position by applying a forgetting factor (). Figure 1 shows the process of position updating for cat_k.

III. GENETIC CAT SWARM OPTIMIZATION

Genetic Cat Swarm Optimization (GCSO) is a hybrid evolutionary technique that combines the effectiveness of GA and CSO. GCSO have strong co-operation of GA and CSO, since it maintains the integration of these two techniques for the entire run. In fact, this kind of updating technique yields a particular evolutionary process where individuals not only improve their score for natural selection of the Cost or for good-knowledge sharing, but for both of them at the same time. To solve an optimization in complex environment Genetic Cat Swarm Optimization is used which overcomes the problem of premature convergence. GCSO is proposed in the field of MIMO detection for the first time. This hybrid algorithm utilizes the uniqueness and usefulness of each algorithm. GCSO have strong co-operation of GA and CSO, also the algorithm exerts the integration of these two techniques for the entire run. This kind of updating technique yields a particular evolutionary process where individuals improve their score for natural selection of the Cost or for good-knowledge sharing at the same time.

The working principle of GCSO is, in each iteration, the population is divided into two parts. The splitting of population is determined by a parameter called hybrid coefficient which determines how the two parts of the population is processed. Each part is taken as the population for GA and CSO respectively and cost is computed for the new set of population. Based on the cost value, the populations are recombined in the updated population which is again divided into two parts in the next iteration for the next run of GA or CSO. This process continues until the Cost value is converged. These processes are combined to form GCSO cycle (Gandelli et al. 2007) and is shown in Figure 3.

An important parameter called hybridization coefficient hcoeff drives the GCSO algorithm. In each iteration hcoeff percentage of the total population is processed by GA and the remaining (1 - h_{coeff}) percentage of the total population is processed by CSO. For example, if h_{coeff} = 0, then the whole population is processed by CSO operators, i.e., the algorithm becomes purely CSO and if hcoeff = 1, then the whole population is processed by GA operators, i.e., the algorithm becomes purely GA. While 0 < h_{coeff} < 1 means the corresponding percentage of hcoeff population is processed by GA and the remaining population is processed by CSO. The effectiveness of GCSO depends upon the parameters selected in GA and CSO and also the hybridization coefficient, which can be static or dynamic.

In case of static hybridization, h_{coeff} is fixed (say 0.3, 0.4, 0.7, 0.9), whereas for dynamic hybridization, h_{coeff} is taken randomly for each iteration as shown in Table II. The fitness function takes the value in the range (0, 1). The goal is to minimize the fitness function. Next the proposed research, how to apply GCSO in MIMO detection is explained.

In order to combine the GA and CSO, initialize the parameters for GA and CSO. Also initialize the hybrid coefficient for GCSO. Generate the initial signal constellation randomly, compute the fitness value for the entire population and check for the fitness value. Here assume, h_{coeff} = 0:3; i.e., 30.

Algorithm: Algorithm for MIMO Detection using GCSO

1. Initialize $MIMO\_POP_{GCSO}$ randomly.
2. Select h_{coeff}: i.e., Static or Dynamic
   Case i: h_{coeff} (k) = 0.4 for all k
   Case ii: h_{coeff} (k) = rand ( )
3. $MIMO\_POP_{GA}$ = h_{coeff} (k) * $MIMO\_P_{GCSO}$ individuals for GA
   $MIMO\_POP_{CSO}$ = (1 - h_{coeff} (k))* $MIMO\_POP_{GCSO}$ individuals for CSO
   Where k is the generation number
4. Update New population
   $MIMO\_POP_{GCSO}$ = $MIMO\_POP_{GA}$ + $MIMO\_POP_{CSO}$
5. Compute the fitness for $MIMO\_POP_{GCSO}$
6. Check for stopping criteria. Repeat steps 3-6 until stopping criteria is satisfied.
7. If stopping criteria are met then
   Symbol = $MIMO\_SYMBOL_{optimum}$.

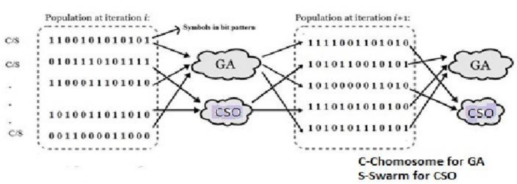


Fig **2. Signal Constellation evolution in GCSO**

TABLE II: HYBRID COEFFICIENT FOR GCSO

h_{coeff} value	**Algorithm**
Static(0)	CSO
Static(1)	GA
Static(0<h_{coeff}<1)	Combination of GA and CSO
Dynamic	Random Value

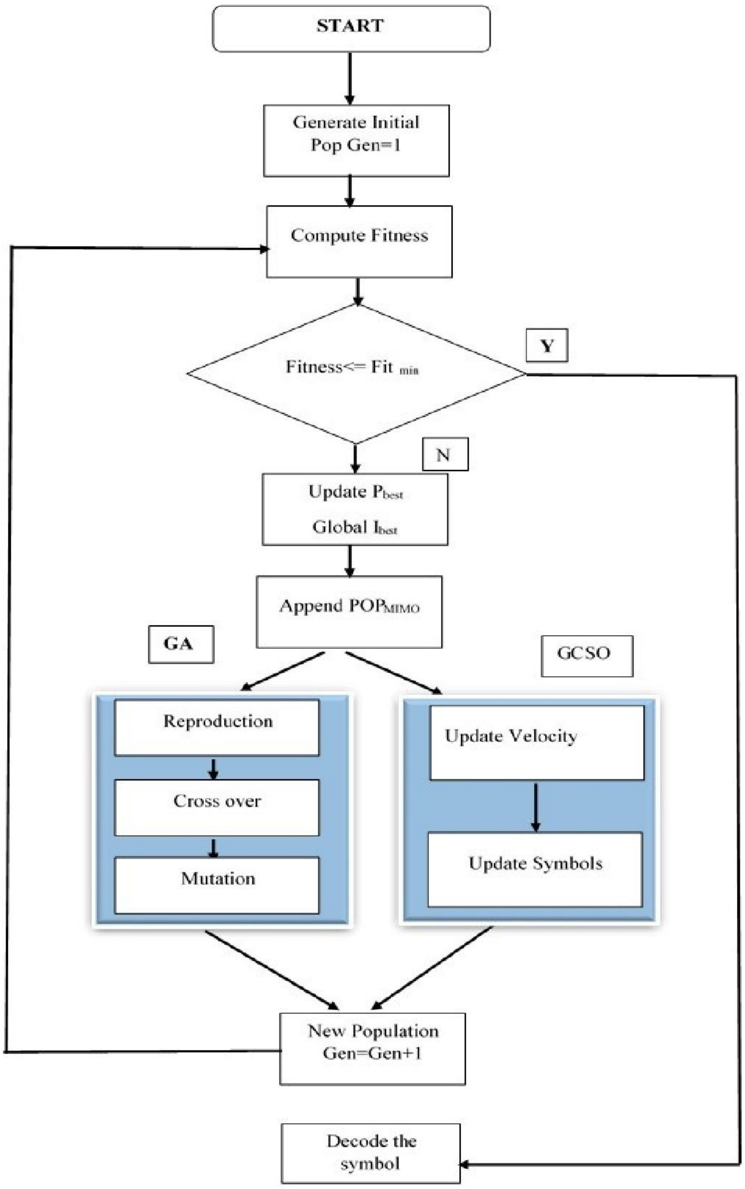


Fig.3. A GCSO cycle for MIMO Detection

TABLE III GA AND CSO PARAMETERS FOR GCSO

GA Parameters	Selection	Proportionate selection
	Mating Scheme	Best Mate Worst
	Crossover Type	Random
	Mutation Rate	0.01
CSO Parameters	Self-recognition parameter(C_1)	1
	Social parameter (C_2)	4-C_1
	Inertia Weight (w)	$0.1<w<0.75$

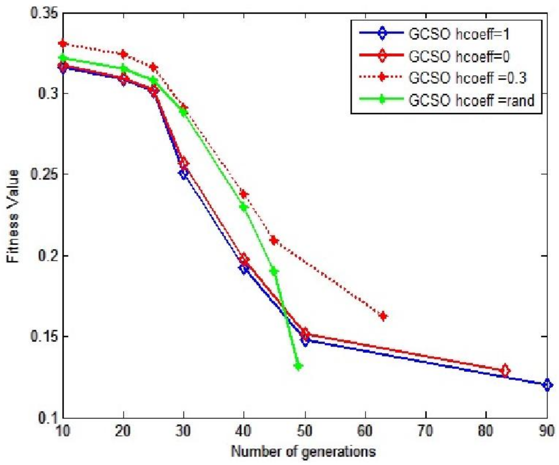
V. RESULT ANALYSIS

Table IV shows the results for MIMO detection using GCSO. The table says that the search space have drastically reduced in case of GCSO with dynamic hybrid coefficient. If hcoeff takes 1 then the algorithm is like GA the search space for symbols to be detected is reduced by 1.1 when compared to SGA (Svac et.al 2012). By properly selecting the GA parameters, the search space has reduced. If hcoeff takes 0 then the algorithm is like CSO the search space for symbols to be detected is reduced by 1.4 when compared to GA. The analysis says that, if the mating scheme is Best Mate Worst and random crossover is selected for GA parameters, variable inertia factor for CSO and dynamic hybrid coefficient, tunes the algorithm to converge at faster rate. Since the best mate Worst mates the best symbol received with the worst symbol received and try to converge the algorithm apace. If h_{coeff} takes static value 0.2 and 0.3 then the search space for symbols to be detected is reduced by 1.8 and 1.3 when compared to GA and CSO respectively. If h_{coeff} takes =0.3, then the performance of SGSO is better.

TABLE IV PREPARATION COMPLEXITY

N_t=N_r	NC	LAS	SGA	ML	SGCSO				
					h_{coeff}(K)=1	h_{coeff}(K)=0	h_{coeff}(K)=0.2	h_{coeff}(K)=0.3	h_{coeff}(K)=rand
8	17	18	4	3	4	3	5	2	2
16	126	146	32	22	30	26	28	27	18
32	964	1156	262	175	148	137	151	121	148
864	7528	9210	2097	1398	1818	1225	977	1058	830

Fig.4. Convergence of GCSO



Since 30 percentage of the population are processed by GA and 70percenatge of the populations are processed by CSO .Dynamically varying hcoeff i.e., random selection of GA and CSO in each iteration the search space for symbols to be detected is reduced by 1.1 when compared to static GCSO. It is found that the local minima may be an issue while convergence but GCSO effectively eliminates the algorithm in getting stuck into local minima. The proposed algorithm effectively decodes the symbol and the BER is also reduced for the decoded symbols.

VI. CONCLUSION

Computational Intelligence is one of the research which reduces the search space where a novel algorithm called Genetic Cat Swarm Optimization is proposed in the field of MIMO detection. The algorithm says it is a good choice in MIMO detection where the receivers search time is reduced in detecting the symbols which is the vantage characteristics of a receiver. The proposed GCSO is a novel algorithm put upon for the first time in the detection of MIMO and successfully detects the symbol in reduced time.

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