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Enhancement of Spectrum Recovery in Cognitive Radio using Artificial Intelligence based on Grey Wolf Optimizer

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Abstract. One of the most promising approaches to meet the demand for radio spectrum is cognitive radio, which enables secondary users to capture the spectrum opportunistically to take advantage of spectrum gaps caused by underuse of frequency spectrum. Secondary users have to sense each band frequently to minimize interference with prime users, which results in a very high computational complexity and hardware cost. Compressive sensing has been suggested as one of the ways to quicken scanning. In this paper, the compressive spectrum sensing recovery process optimization challenge can be resolved using different artificial intelligence algorithms such as a Gravitational Search Algorithm and Hybrid Particle Swarm Optimization_Gravitational Search Algorithm. One of the newest meta-heuristic optimization algorithms is the Grey Wolf Optimizer, which can solve the optimization problem of the compressive spectrum sensing recovery process. The simulation results in this research compared between the performance of algorithms for detecting the spectrum and demonstrated the grey wolf optimizer algorithm's performance that the ratio of accuracy in the spectrum recovery process reaches to 100 % at a positive Signal-to-Noise Ratio in comparison to another algorithms, the predictive approach of the modified- basis pursuit denoising and the weighted approach.

Keywords: cognitive radio, compressive sensing, optimization, GSA, PSOGSA, GWO

1. Introduction

The electromagnetic radio spectrum is a natural resource. To better utilize this priceless natural resource, Cognitive Radio (CR) is used. In order to provide reliable communication and effective utilization of the radio spectrum, Haykin defined CR as an intelligent digital radio that comprehends the environment so can operate and modify radio parameters accordingly (Haykin, 2005). According to research (Akyildiz & Mohanty, 2006), because Primary Users (PUs) or licensed users don't always use their channels, the frequency spectrum is underutilized. By utilizing available spectrum, Secondary Users (SUs) can access and communicate. SUs must continuously scan the spectrum to discover spectrum gaps that are not being used by the PUs that are registered by them for preventing PU interference. Detection of a broad spectrum improves the likelihood of SU of finding unoccupied bands by searching a larger frequency range (Javed & Shabbir, 2019). The Nyquist theorem states that high sampling rates are required to sample the spectrum, this place hardware limitations based on the required high-speed Analogue to Digital Converter (ADC) that produces increasing in communication overhead on the SU terminals.

Compressive sensing (CS) (Candès & Wakin, 2008) has been used effectively to reduce the costs associated with data gathering in a variety of application areas, including wireless communication (Tian & Giannakis, 2007). It samples the spectrum at sub-Nyquist sampling rate using an Analogue to Information Converter (AIC) (Kirolos & Baraniuk, 2006). Many approaches were proposed to lower the sample rate such that using geo-location database information (Qin & Parini, 2015) and many approaches used the primary user channel occupancy as a prior information that to increase the spectrum sensing efficiency (Khalfi & Zorba, 2018). At SU, a low sample rate and fewer measurements are used to reconstruct the spectrum using CS. The initial CS approaches assume that there is only one known aspect of the signal, its sparsity (Donoho, 2006). Knowing statistical information of the signal could help in CS recovery process. Incorporating regularization terms with signal value estimations and partial support information is one method for CS that uses side information (Vaswani & Zhan, 2016). Assuming a slow fluctuating nature of the signal support in Magnetic Resonance Imaging (MRI), information from the prior time instant iteratively aids the reconstruction algorithm in capturing the sparse solution with fewer samples. It was suggested in (Vaswani & Lu 2010) to use a modified Basis Pursuit (BP) method that merges known support elements using a weighted $l1$ minimization method with zero weights on the known support in the noise-free case, and then extending the method for the noisy case, which is known as regularized modified Basis Pursuit Denoising (reg-mod-BPDN) (Lu & Vaswani, 2011). Channel occupancy modelling can improve spectrum sensing by letting SUs anticipate PU occupancy (Barnes & Maharaj, 2014). To estimate the idle and busy states holding duration, a time domain occupancy model can be modelled with a continuous time semi-Markov chain (CTSMC) with any distributions (López Benítez & Casadevall Palacio, 2010). The frequency domain model was built using numerous measurement campaigns, and the appropriate model for it was the beta distribution (Wellens & Mähönen, 2010). The Basis Pursuit De-Noising (BPDN) optimization problem and the more popular Least Absolute Shrinkage and Selection Operator (LASSO) are very similar (Emmanuel & Tao, 2005). Several other alternative CS recovery approaches were presented as a predictive strategy using modified-BPDN and a forecast of the occupancy the PU's patterns (Eltabie & Abdelkader, 2019), Another method in this research that extracts occupancy probability for each channel utilizing statistical data about the channel in order to solve a weighted compressive sensing reconstruction problem (Khajehnejad & Hassibi, 2011).

Artificial Intelligence (AI) applications in wireless communications have recently received a lot of interest. AI has shown considerable success in the areas of speech recognition, image recognition, demonstrating its enormous promise in solving issues that are difficult to model (Wang & Shi, 2020). AI approaches have emerged as a crucial facilitator in the effort to address the rising demand for wireless communications. There are many optimization techniques have been used in the wireless communication such as Particle Swarm Optimization (PSO) (Marini & Walczak, 2015) which a swarm of particles that can move about the parameter space is used to illustrate the collection of potential solutions to the optimization problem, setting trajectories based on their own and neighbor's best performances. Another technique is a Gravitational Search Algorithm (GSA) which is regarded as an innovative optimization method based on the laws of gravity and mass interaction (Rashedi & Saryazdi, 2009). PSO and GSA are combined to create a new hybrid population-based algorithm called PSOGSA (Mirjalili & Hashim, 2010). The major goal is to combine the strength of both algorithms by integrating the exploitation capability of PSO with the exploring capability of GSA that uses a low-level coevolutionary heterogeneous hybrid to combine PSO with GSA. The most appropriate technique that we apply in the optimization problem is a Grey Wolf Optimizer (GWO) (Mirjalili & Lewis, 2014) which is a brand-new metaheuristic algorithm that falls within the third classification. The method of hunting used by grey wolves served as the model for this algorithm. The four different subtypes of grey wolves: alpha, beta, delta, and omega are utilized to simulate the hierarchy of command. In addition, the three fundamental hunting techniques used are looking for prey, surrounding prey, and attacking prey.

In this paper, we consider CR network, and we need to recover the spectrum by using optimization techniques such as GSA, PSOGSA and GWO algorithms for solving the optimization problem of the spectrum recovery process and show the performance of these techniques and then compared the performance of GWO algorithm with the predictive of the modified-BPDN approach and the weighted approach.

2. System Model and Research Methodology

We consider a CR system where a singular SU that senses a sparse wideband spectrum of V non-overlapping channels. While assuming that the number of active PUs is random, the power level of the PU in each channel is unknown and the channel between each PU and the SU is an Additive White Gaussian Noise (AWGN) channel. Consider U occupied PUs, whose signals are characterized by s_u where $u \in [1:U]$. The signal that received by the SU terminal can be represented as follows

$$x = \sum_{u=1}^{U} h_u * s_u + w \tag{1}$$

Where h_u is the gain in the channel from the u_th PU to the SU, '*' indicates convolution, and w is the additive white Gaussian noise (AWGN) at the SU. By applying Discrete Fourier Transform (DFT) to eq. (1) we can obtain the frequency spectrum of the received signal as

$$X = \sum_{u=1}^{U} H_u S_u + W \tag{2}$$

Where H_u is an $V \times V$ diagonal matrix and X, S_u, W are the DFT transformation of x, s_u, w respectively. Eq. (2) could be formed in a matrix form as

$$X = HS + W \tag{3}$$

Where S denotes the transmitted signal and X is an $V \times 1$ vector that represent the received spectrum at the SU. The SU needs to sample the received signal in order to capture the spectrum S. In comparison to using an ADC, which requires the signal to be sampled at Nyquist rate, an AIC could be used to sample the signal with a minimal number of samples. The AIC can sample a sparse spectrum with a compression ratio of (Z/V) that the number of occupied channels U is substantially fewer than the total number of channels V. The compression ratio is characterized as the number of compressed measurements divided by the total length of the sparse signal that collect Z measurements.

The samples measurement vector y could be represented as $Z \times 1$ vector where $(U < Z << V)$ as follows

$$y = \varphi x = \varphi F^{-1} X \tag{4}$$

where φ is the $Z \times V$ measurement matrix and F^{-1} is the $V \times V$ inverse DFT matrix.

3. The Behavior Model of the PU

To simulate the observed durations of busy and idle periods, (Lopez-Benitez & Casadevall, 2013) demonstrated that the Generalized Pareto (GP) distribution is a well-suited fit for channel occupancy modelling for numerous radio technologies, especially in low-time resolution data which the Cumulative Distribution Function (CDF) of the state holding time T under this distribution is given by:

$$F_{GP}(T\,;\mu\,;\lambda\,;\alpha) = 1 - \left[1 + \frac{\alpha(T-\mu)}{\lambda}\right]^{-1/\alpha} \tag{5}$$

Where T is the length of the time period and $\mu\,,\lambda\,,\alpha$ are the location, scale, and shape parameters, respectively. These characteristics meet that.: for $\alpha \geq 0\,, T \geq \mu$ and for $\alpha \leq 0$, $\mu \leq T \leq \mu - \frac{\lambda}{\alpha}$.

The following formula can be used to determine the state holding times' average $\mathrm{E}\{T\}$ according to GP distribution:

$$\mathrm{E}\{T\} = \mu + \frac{\lambda}{1-\alpha} \tag{6}$$

We employed a Continuous-Time Semi-Markov Chain (CTSMC) (López-Benítez & Casadevall, 2012) to simulate the behavior of the PU in each channel, in which the time index is supposed to be continuous. We suppose that a sparse spectrum of V nonoverlapping frequency channels. The channels were grouped into M groups and each channel has a Duty Cycle (DC) ψ_i where $\psi_i \in \{\psi_1, \psi_2, \psi_3, \ldots, \psi_M\}$ and in order to create a sparse domain, we establish a low average DC, which can be defined as the average probability of the channel being busy throughout time and represented by

$$\psi = \frac{\mathbb{E}\,(T_{busy})}{\mathbb{E}\,(T_{busy}) + \mathbb{E}\,(T_{idle})} \tag{7}$$

Where $\mathbb{E}\,(T_{busy})$ is the mean value of busy periods and $\mathbb{E}\,(T_{idle})$ is the mean of idle periods. The wideband spectrum is divided into multiple band blocks based on their frequency. the Beta distribution was found to be the best fit to model a group's DC (Wellens & Mähönen, 2010). The probability density function of the Beta distribution is formed as

$$F(x;\alpha,\beta) = \frac{1}{B(\alpha,\beta)}\, x^{\alpha-1}(1-x)^{\beta-1} \tag{8}$$

$$B(\alpha,\beta) = \int_0^1 t^{\alpha-1}(1-t)^{\beta-1}dt \tag{9}$$

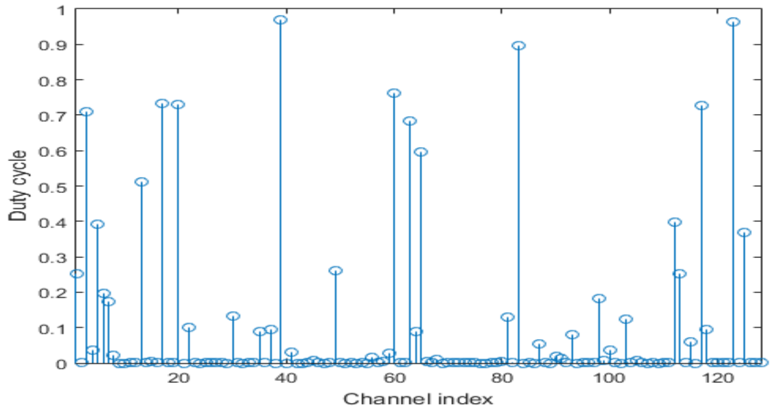


Fig. 1: DCs for Beta distribution parameters at $\alpha = 0.1, \beta = 0.85$

Figure 1. shows the simulated PU traffic pattern for parameters $\alpha = 0.1 \; and \; \beta = 0.85$ over 100-time instances. For CTSMC model, the state s_0 denoted as the channel being idle and hence available for the SU to use it and the state s_1 on the other hand, indicates that the channel is active with PU and a sample period T_s as demonstrated in Figure 2, can provide a series of states s_1 and s_0 for the channel when it is active or inactive.

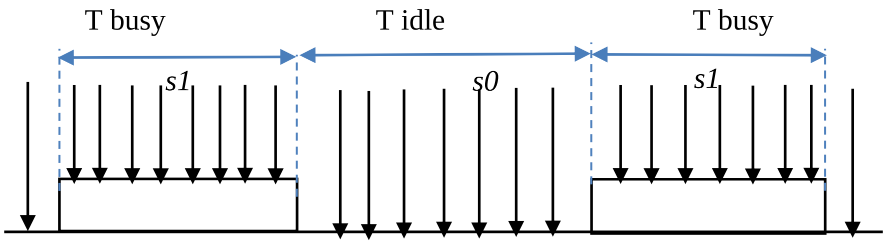


Fig. 2: Channel conditions over a period

4. Spectrum Recovery

There would be an infinite number of solutions for the system equation (4) because the number of rows Z is lower than the number of columns V of the sensing matrix, but we are only interested in the sparsest solution that is the minimization of $\|x\|_{l0}$ which is an NP-hard problem. Relaxing the problem to a $l1\_norm$ minimization, this usually leads to the sparsest solution, by solving the following convex BP optimization problem as in (Chen & Saunders, 2001).

$$\min_x \|x\|_{l1} \; subject \; to \;\; y = \varphi \, x \tag{10}$$

This problem is converted to a Lagrange variant known as the BPDN that assuming a noisy observation environment as following

$$\min_x \|x\|_{l1} + \lambda \, \|y - \varphi \, x\|_{l2}^2 \tag{11}$$

Where λ is a penalty parameter that can be utilized to compare and contrast between spectrum sparsity enforcement and $l2$ norm term minimization.

The CR detects a compressed collection of spectrum measurements and recursively recovers the spectrum. Several methods for CS spectrum recovery were presented such as the BP denoising (BPDN) approach (Emmanuel & Tao, 2005) and the Modified BPDN (mod-BPDN) approach (Lu & Vaswani, 2010). In approach (Emmanuel & Tao, 2005) by assuming that the values of DC for each channel of the spectrum are known, the PU arrival and leaving could be simplified by a two-state discrete time Markov chain (DTMC) and the transition probabilities of the transition matrix could be described to forecast each channel's upcoming state by:

$$P = \begin{bmatrix} 1-\psi & \psi \\ 1-\psi & \psi \end{bmatrix} \tag{12}$$

By forecasting a partial support information from the preceding sensing instant, they employ the statistical occupancy model for the Modified BPDN (mod-BPDN) approach to enhance the performance of the CS spectrum recovery (Eltabie & Abdelkader, 2019). Consider *Supp (St)*, which represents the spectrum support in time t and D_t represent the index of this support. The (mod-BPDN) recovery problem (Lu & Vaswani, 2010) could be represented by:

$$\min_x \|x\, D_t\|_1 + \lambda\|y - \varphi x\|_2^2 \tag{13}$$

Another approach in this research is employing a weighted CS technique as an alternative to such channel band prediction, where applying a weight to each channel based on its occupancy using the channel occupancy model. The weighted optimization problem could be formed as:

$$\min_x \|x\|_{w1} + \lambda\|y - \varphi x\|_2^2 \tag{14}$$

Where $\|x\|_{w1}$ is a weighted l_1 norm provided by:

$$\|x\|_{w1} = \sum_{i=1} w_i\, |x_i| \tag{15}$$

In the optimization problem (15), the weights selected represent the likelihood of an idle channel.

5. Optimization Process

5.1. Gravitational Search Algorithm

The performance of agents is determined by their mass, which is treated as an object. Gravity acts as an attraction between all the items, and this attraction generates an overall movement of all objects in the direction of the items having higher mass. As a result, gravitational pull serves as a direct channel of communication between masses.

- **The gravitational law:** Every particle pulls in the opposite direction of every other particle and the gravitational force between two particles is inversely proportional to their separation and directly proportional to the sum of their respective masses.
- **Movement law**: Any mass's present velocity is equal to the product of its variation in velocity and the proportion of its prior velocity (Rashedi & Saryazdi, 2009). The following are the several steps of the suggested algorithm:

a) Identifying the search space.
b) Initialization using random numbers.
c) Assessment of agents' fitness.
d) update the gravitational and inertial masses.
e) the overall force in various directions being calculated.
f) acceleration and speed calculations.
g) Positioning the agents.
h) In order to reach the stop criterion, repeat steps c through g.
i) End.

5.2. Hybrid PSOGSA

- PSO and GSA are combined to create a new hybrid population-based algorithm called PSOGSA (Mirjalili & Hashim, 2010). The major goal is to combine the strength of both algorithms by integrating the exploitation capability of PSO with the exploring capability of GSA that uses a low-level coevolutionary heterogeneous hybrid to combine PSO with GSA. The fundamental concept behind PSOGSA is to integrate PSO's social thinking (g_{best}) capabilities with GSA's local search functionality.
- The PSOGSA update process takes into account the fitness. The brokers approach sensible answers entice the other agents that are scouring the search arena by offering incentives to them. When every agent is close to an excellent answer, they move very slowly. In this instance, the g_{Best} aid in their exploitation of the world's best. PSOGSA uses a memory (g_{Best}) to store the top solution thus far, making it available at any moment. The best answer found thus far can be seen by each agent, and they will all tend to it (Magdy & Hamed, 2015). The PSOGSA process is depicted by the figure 3.

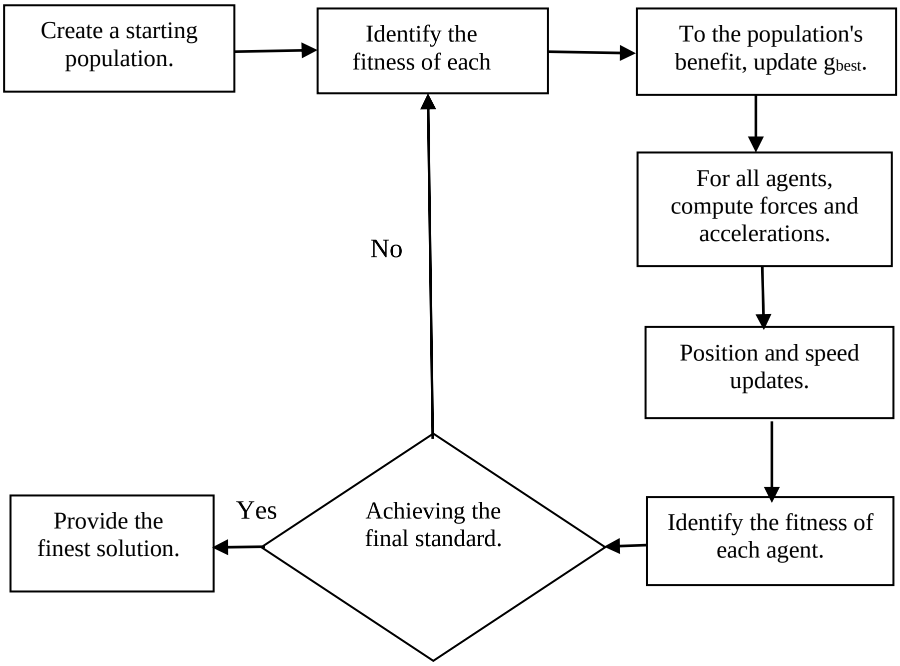


Fig. 3: PSOGSA's fundamental flowchart

5.3. GWO Algorithm

The GWO optimization method begins with the creation of a random grey wolf population (candidate solutions). The wolves α, β, and δ appreciate the likely where the prey is located across the iterations (optimum solution). Grey wolves adjust their positions according on how far away they are from their prey (Bozorg-Haddad, 2018).

We can solve the optimization problem by using GWO which was introduced by Mirjalili as one of the brand-new meta-heuristic techniques for optimization. The leadership hierarchy is simulated using four different breeds of grey wolves, including alpha, beta, delta, and omega. Additionally, the three essential components of hunting including looking for prey, surrounding prey and attacking prey are used.

In the GWO algorithm, the concept of social hierarchy aids in grading and saving the best answers up to the current iteration. The following is a summary of some notes:

- The encircling mechanism creates a two-dimensional circle-shaped neighbor and the solution.
- Grey wolves (candidate solutions) use the random parameters to build different hyper-spheres with random radii.
- The GWO algorithm's hunting technique allows grey wolves (candidate solutions) to choose the most likely location of the prey (optimum solution).

- The adjustable values of the parameters in the GWO algorithm ensure exploration and exploitation, as well as a smooth transition between exploration and exploitation.

GWO pseudocode:

Start

Create the grey wolf colony from scratch.
Initialize the parameters (number of grey wolves, number of iterations, etc.)
Determine the search agents' fitness values and assign them a grade.
t=0
While (t < Max number of iterations)
  For every searcher
    Update the search agent's position at the moment.
  End for
Update the parameters (number of grey wolves, number of iterations, etc.)
Determine the search agents' fitness values and assign them a grade.
t=t+1
End while

End

6. Simulation Results and Discussions

Consider a spectrum with $V = 128$ sub-channels, Beta distribution model is assumed to sample the DC values ψ for the V subchannels by the parameters $\alpha = 0.1 \ and \ \beta = 0.85$ of the E-GSM 900 UL band (López-Benítez & Casadevall, 2012) that result the average DC value of 0.1. we generate the generalized Pareto (GP) distribution to simulate the apparent durations of the busy and idle times by the parameters $\mu_{ON} = 100 \ ms \ , \lambda_{ON} = 300 \ ms \ and \ \alpha_{ON} = \alpha_{OFF} = 0.25$. the DC value of each channel is used to determine additional parameters for the idle state holding times as: $\mu_{OFF} = \mu_{ON}\left(\frac{1}{\psi} - 1\right), \lambda_{OFF} = \lambda_{ON}\left(\frac{1}{\psi} - 1\right)$. An additive white Gaussian noise corrupts the received signal ,the Signal to Noise Ratio (SNR) is defined as the signal power over the whole bandwidth normalized by the noise power. the compression ratio (cr) is the proportion of the number of measurements Z to the signal's dimension V. The simulation results are presented in the following figures.

As we apply different algorithms of optimization such as GSA and PSOGSA in our simulation to solve the minimization problem of the spectrum recovery process with number of agents equal to 30 and maximum number of iterations equal to 500, the performance of the algorithms didn't achieve the target of detection enhancement as shown in figure.4, as the probability of detection didn't reach a high rate. So, we had to resort to another technique of optimization to solve this minimization problem.

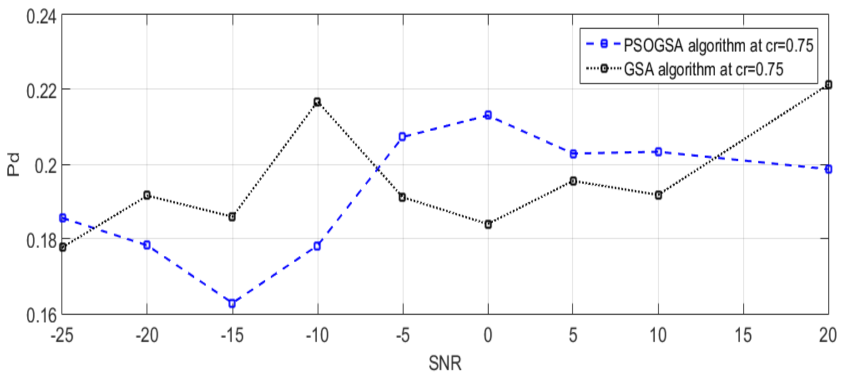


Fig. 4: Probability of detection for GSA and PSOGSA algorithms at various SNR levels in dB at probability of false alarm =0.1 and at compression ratio of cr =0.75

Then we consider in our simulation of the GWO algorithm with the number of search agents equal to 30 and the maximum number of iterations equal to 500.The detection accuracy with different SNR values is shown in Figure.5 at cr equal to 0.2 and 0.75. the results show that the GWO algorithm achieves superior performance for the detection probability compared with predictive and weighted approaches (Eltabie & Abdelkader, 2019). At cr equal to 0.2 and SNR equal to -25 the probability of detection (Pd) was very low until SNR reaches to -20 that Pd begin to increase and achieves the maximum value at SNR equal to -15. At cr equal to 0.75, the Pd achieves perfect accuracy for more range of SNR.

In the Figure.6. the variation in detection at various compression ratio levels at the same probability of false alarm of 0.1 at SNR equal to -25 dB and 25 dB. As shown when SNR equal to -25 the Pd of the GWO algorithm was very low and couldn’t improve by increasing cr. But at SNR equal to 20 dB, the GWO algorithm achieves the highest level of detection compared with predictive and weighted approaches that Pd reaches to the maximum value over all range of the compression ratio in the GWO algorithm.

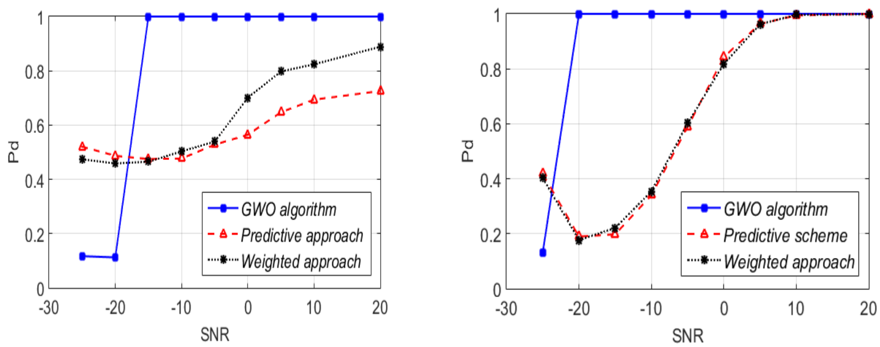
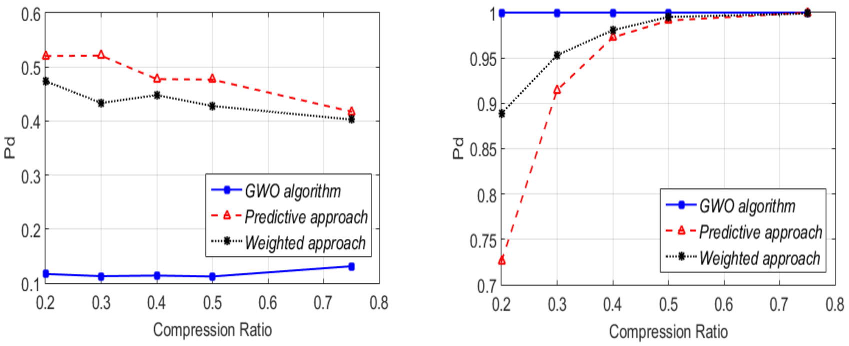


Fig. 5: Probability of detection at various SNR levels in dB at probability of false alarm =0.1 and at compression ratio of (a) cr =0.2 and (b) cr =0.75



(a) **(b)**

Fig. 6: Probability of detection at various compression ratios at probability of false alarm =0.1. and at (a) SNR = -25 dB and (b) SNR= 20 dB

The Pd for the spectrum recovery process at cr equal to 0.75, using predictive scheme and weighted scheme was better than another optimization techniques at SNR equal to -25 dB. But when SNR begins to come up, the performance of GWO algorithm improve and Pd reaches the max value at SNR equal to -20 and over a long range of SNR from -20 to 20 dB as shown in table.1. And as shown the performance of GSA and PSOGSA didn’t improve at any value of SNR, while the Pd for the predictive scheme and weighted scheme reaches the max at SNR equal to 20 dB only.

Table 1: Pd for the spectrum recovery process using GSA, PSOGSA, predictive scheme, weighted scheme and GWO algorithm at cr = 0.75

Algorithm	SNR								
	-25	-20	-15	-10	-5	0	5	10	20
GSA	0.169	0.155	0.143	0.151	0.160	0.173	0.167	0.173	0.158
PSOGSA	0.185	0.178	0.163	0.179	0.209	0.213	0.204	0.205	0.200
Predictive Scheme	0.420	0.200	0.200	0.340	0.590	0.850	0.960	0.990	1.000
Weighted Scheme	0.400	0.200	0.210	0.350	0.600	0.830	0.960	0.990	1.000
GWO	0.120	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000

7. Conclusion

In this paper, we incorporate AI based on GSA, PSOGSA and GWO algorithm to solve the minimization problem for the spectrum recovery process in compressive sensing. Additionally, it is compared to the predictive method, which forecasts traffic for the PU and uses it as background information for compressive sensing and the weighted algorithm, which solving the minimization recovery problem by extracting the value of DC for each band. The simulation results and discussions showed that the GWO algorithm has more performance and capability to solve the minimization problem for the spectrum recovery process, that the ratio of accuracy reaches to 100 % at a long range of SNR from -20 dB to 20 dB in comparison to another algorithms, that the predictive scheme and the weighted scheme reached to this accuracy only at SNR equal to 20. As can be seen, our proposed technique achieves superior performance compared with another approaches.

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