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An Efficient Genetic Approach for Subcarrier and Power Allocation of Cognitive Network

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Abstract— In Cognitive Radio (CR) networks, different unlicensed users may acquire different available channel sets with the licensed users. This non-uniform spectrum availability imposes special design challenges for broadcasting in CR. As dynamic allocation of spectrum increase the demand of perfect utilization system. In this paper a two phase learning teacher learning based optimization algorithm was used. Here chromosome of the PU and SU units are paired with available channels for efficient communication. As algorithm make changes based on the objective function so results obtained are much better as compare to the previous work HGA.

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Keywords— *Annotation, Image retrieval, Feature extraction, Re-ranking, Visual contents.*

I. Introduction

In long distance communication, we have many factors that are affecting the signal in many ways. Fading is the phenomenon that occurs due to the collisions of the signal in the path of destination .not only this; we also have noise and interference patterns that are affecting the overall system considerably. We need to make their effect to a minute level, such that there will be no transmission errors occurring in transmission and after reception too. In order to reduce the noise effect, we go for introducing the concept of relays. Relays are the intelligent transceivers, that are in between the path of source and destination, where the signal is been sent to the destination through the help of relays. So a new approach called, Decode-and-forward criteria. This concept is used in relays and in order to reduce the interference pattern.

Here, signals are frequency modulated first and these signals are again made to be like orthogonal to each other having guard interval. This reduces the Inter-symbol Interference up to a greater extent, which is been a major issue in communications. So by implementing these, we go for efficient utilization of system resources by considering some of the factors. An algorithm to select the best transmits way between the network nodes. The algorithm can select direct, dual or diversity transmission based on the available spectrum as well as the maximum allowable transmission powers. The systems are considering single carrier channels. Proposed an algorithm to select the best transmit way between the network nodes. The algorithm can select direct, dual or diversity transmission based on the available spectrum as well as the maximum allowable transmission powers. The systems are considering single carrier channels proposed an algorithm to select the best transmit way between the network nodes. The algorithm can select direct, dual or diversity transmission based on the available spectrum as well as the maximum allowable transmission powers. The systems are considering single carrier channels. A Cognitive radio (CR) has been proposed to solve the spectrum under-utilization problem by allowing a group of secondary users (SU) to access the unused radio spectrum originally allocated to the primary user (PU). The CR performance and the spectrum utilization can be further improved by using the cooperative communications in which several relays are used to assist the source to destination transmission.

Cognitive radio, with the ability to flexibly adapt its transmission parameters, has been considered as a revolutionary technology to dynamically access the under-utilized wireless spectrum [1]. In order to fully utilize the spectrum resources, efficient dynamic spectrum allocation and sharing schemes are very important. Novel spectrum access control protocols and control channel management should be designed to accommodate the dynamic spectrum environment while avoid collision with a primary user. When a primary user re-appears in a licensed band, a good spectrum handoff mechanism is required to provide secondary users with smooth frequency transition with low latency. In multi-hop cognitive wireless networks, intermediate cognitive nodes should intelligently support relaying information and routing through using a set of dynamically changing channels. In order to manage the interference to the primary users and the mutual interference among themselves, secondary users' transmission power should be carefully controlled, and their competition for the spectrum resources should also be addressed.

II. Related Work

In [6] discussed about subcarrier and power allocation problem for orthogonal frequency division multiple access based on relay. The joint optimized problem is defined in terms of power allocation, subcarrier assignment and relay selection. The above problem is solved by two techniques such as sub gradient method and dual decomposition. The objective of technique is to improve the throughput. Two low-complexity suboptimal schemes are introduced for reducing the computational cost. The above schemes are tested by computer simulations which are based on LTE-A network. The proposed schemes also support heterogeneous services which meets the Qos. Relay selection and resource allocation supports GBR and AMBR traffic in a multi-user cooperative OFDMA-based uplink system. Three schemes are proposed such as QoS aware optimal joint relay selection, subcarrier assignment and power allocation which are under a total power constraint. A joint optimization problem has been investigated in order to achieve the maximum throughput by satisfying QoS requirements of individual user for relay selection and resource allocation. The computational complexity was reduced with the help of suboptimal schemes. Advantages of paper [6] are it maximizes the system throughput. But doesn't meet the Qos requirement.

In [7] Cooperative spectrum sharing scheme increase the spectrum usage effectively by permitting secondary users(SUs) to share the licensed bands with primary users(Pus) in dynamic and opportunistic manner. This paper discussed about how one PU and one SU realize an efficient spectrum sharing scheme via dynamic non-cooperative bargaining. The PU does not have the complete information about SU's energy cost which is one of the key challenges in this paper. Advantage of this paper [7] is, it has higher data rate but increases bargaining power consumption. Sensing based spectrum sharing technique combines the benefits of both spectrum overlay and spectrum underlay to improve the throughput of the secondary user, without generating harmful interference to the primary user.

In 2014, Ghazzai et al [1] developed a formulation for the optimization problem to increase the gain pertaining to the Long-Term Evolution cellular operators and reducing the green house gas (CO2) emission. They have proposed the methods, which work on the basis of Genetic algorithm as well as the Particle Swarm optimization, to cut down the energy utilization in base stations to a lowest level by optimizing the sufficient energy that are procured from the retailers.

Monteiro et al [3] has proposed an power management algorithm for the maximizing the minimum MOS of the wireless users at the same time focused on the Quality of service for the resource allocation. Experiment is done on the simulator for the study of the proposed model. It was obtained in the results that proposed system has heavily reduced the loaded system.

In [9] The main motivation for the HGA framework comes from the idea that it can reduce the impact of extra assumptions made in previous works to simplify the problem. In our HGA, the chromosome is divided into an integer string for subcarrier pairing and a real-number string for power allocation.Two new initialization methods of these chromosomes, which are motivated by the convex optimization theory, are proposed. New crossover and mutation schemes are also devised to accommodate these new chromosomes, as well as to manage the interference to the PUs. Furthermore, we also propose a two-stage low-complexity genetic algorithm, which separately determines the proper subcarrier pairs and power allocations.

III. Proposed Methodology

Generate Population

Here assume some chromosome set that are the combination of different pairs k, m and power allocation unit. This is generate by the random function which select fix number of values. This can be understand as let the number of pairs be t_k and t_m. In the similar fashion other possible solutions are prepared which can be utilize for creating initial population represent by ST matrix.

$$ST[x] \leftarrow Random(N, t)$$

Table 1 Representation of ST[] matrix (Subcarrier).

Subcarrier Pairing			
t_k		**t_m**	
1	3	2	4
4	2	1	3
1	4	3	2
3	2	4	1

I.

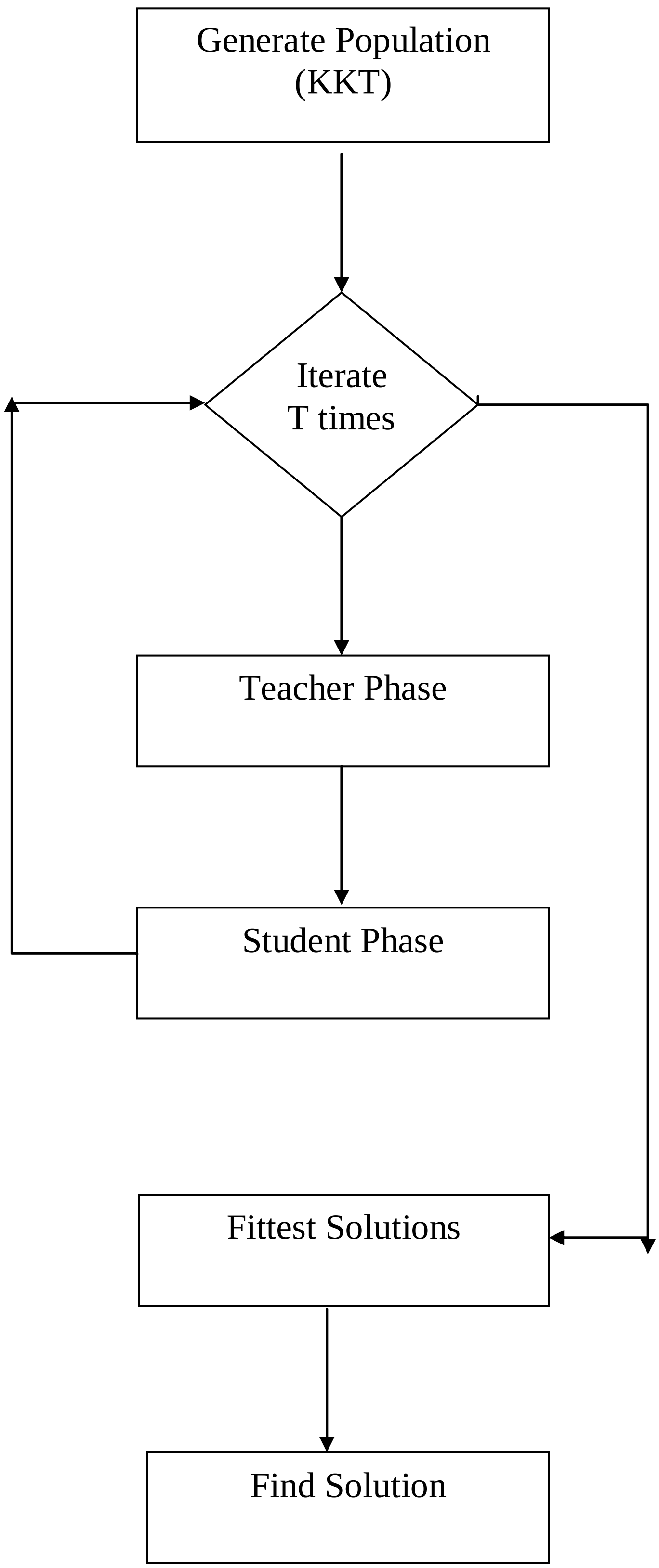

Fig. 1 Proposed work Block diagram.

Table 2 Representation of PT[] matrix (power).

Power Band			
P_k		P_m	
0.1	0.3	0.2	0.4
0.4	0.2	0.1	0.3
0.1	0.4	0.3	0.2
0.3	0.2	0.4	0.1

$$PT[x] \leftarrow Random(N, t)$$

This work propose another initialization scheme with complexity lower than that of the previous scheme. First, we only run a few iterations among power allocation and dual variables and for a baseline parent chromosome. We name the resulting dual variables for this baseline chromosome as γ_{bS} , γ_{bR}, β_{bS}, and β_{bR}. As for the rest of the parent chromosomes, we randomly generate the power allocation and subcarrier pairing but select the good ones by the KKT residues using γ_{bS} , γ_{bR}, β_{bS}, and β_{bR}. The KKT residue is a measure of the distance between a solution and the KKT solution (the solution satisfies the KKT conditions that are necessary for optimality [19]), and only the parent chromosomes with power allocation and subcarrier pairing close to the KKT solutions are selected. The randomly generated parent chromosome is accepted only when its KKT residue is sufficiently small. For the power allocation part of a parent chromosome, it must satisfy the interference constraints and for the PU.

Teacher Phase

For finding difference two function are use first is Eludician Distance formula other is cosine similarity function

The Euclidean distance d between two solution X and Y is calculated by

d = [SUM((X-Y).^2)]^0.5

The Cosine distance d between two vectors X and Y is

d = [1 – (X*Y' / √(X*X')* (Y*Y'))]

Following Step will find distance between the selected population for finding the teacher in the population.

1. Loop x = 1:ST
2. Loop n = 1:N
3. D[n, x] = Dist(Ds[n], x) // Here Dist is a Euclidean function
4. endLoop
5. endLoop
6. S←Sum(D) // Sum matrix rowwise
7. [V I]←Sort(S) // Sort matrix in increasing order

So the matrix D contain all the values of the centriod distance from the document then find the minimum distance which will evaluate specify best possible solution.

S←Sum(D) // Sum matrix rowwise
[V I]←Sort(S) // Sort matrix in increasing order

Top possible solution after sorting will act as the teacher for other possible solutions. Now selected teacher will teach other possible solution by replacing fix number of values as present in teacher solution. By this all possible solution which act as student will learn from best solution which act as teacher.

Main motive of this step is to find best solution from the generated population. Here each possible solution is evaluated for finding the distance from each node or power so that pair closer to the best pairr. Then calculate the fitness value which give overall rank of the possible solution.

A good teacher is one who brings his or her learners up to his or her level in terms of knowledge. But in practice this is not possible and a teacher can only move the mean of a class up to some extent depending on the capability of the class. This follows a random process depending on many factors. Let Mi be the mean at any iteration i. The teacher will try to move mean Mi towards his/her own level so the new mean will be designated as Mnew. The solution is updated according to the difference between the existing and the new mean given:

Difference Meani = ri * (Mnew – Tf *Mi)

Where Tf = teaching factor.

Teaching factor (Tf) decides the value of mean to be changed, and ri is a random number in the range [0, 1]. Tf is not a parameter of the algorithm and its value is not given as an input to the algorithm. The value of TF can be either 1 or 2, which is a heuristic step and decided randomly with equal probability as,

TF = round [1 + rand(0, 1)]

This difference modifies the existing solution according to the following expression

Xnew,i = Xold, i + Difference Meani,i

Where Xnew,i is the updated value of Xold,i. Accept Xnew,i if it gives better function value.

Student Phase

In this phase all possible solution after teacher phase are group for self learning from each other. This can be understand as let group contain two student then each student who is best as compare to other will teach other solution. Teaching is similar as done in teacher phase, here replacing fix number of centroid is done which is similar as in best student of the group.

1. For i = 1: Pn
2. Randomly select two learners Xi and Xj, where i is not equal to j
3. If f (Xi) < f (Xj)
4. Xnew, i = Xold, i + ri (Xi − Xj) (for a minimization problem)
5. Else
6. Xnew, i = Xold, i + ri (Xj − Xi)
7. End If
8. End For

Accept Xnew if it gives a better function value. Once student phase is over then check for the maximum iteration for the teaching if iteration not reach to the maximum value then GOTO step of teacher phase else stop learning and the best solution from the available population is consider as the final centroid of the work. Now documents are cluster as per centroid.

Fittest Solution

So final set of chromosomes which comes out after the iteration of the teacher learning based optimization is evaluate to find the fittest one. As this fittest act the final solution of the proposed work.

$$\frac{1}{2}\sum_{k=1}^{Z_S}\sum_{m=1}^{Z_S} t_{k,m}\log(1+H_{k,m}p_{k,m})$$

Above equation act as the fitness function as well as this can obtain from the [9]. Here Zs is number of units at sender and receiver side. While $H_{k,\,m}$ is the normalized channel gain at the relay and destination side.

IV. Experiment and Results

This section presents the experimental evaluation of the proposed teacher learning based optimization algorithm for power and subcarrier allocation with previous work Hetrogeneous Genetic Algorithm (HGA) done in [9]. All algorithms and utility measures were implemented using the MATLAB tool. The tests were performed on an 2.27 GHz Intel Core i3 machine, equipped with 4 GB of RAM, and running under Windows 7 Professional.

Results

Table 3 Execution time comparison of HGA and proposed work.

Execution Time in Second		
PU-SU sets	HGA	Proposed Work
5-3	2.71557	1.2506
8-4	4.68627	1.76
12-5	7.68627	2.02015

From above table 3 it is obtained that proposed work Teacher Learning Based optimization genetic algorithm required less execution time as compare to the previous HGA [9] work. This is due to the dual learning in TLBO which consider the objective function which learning as well.

Table 4 Execution time Comparison of HGA and proposed work.

Channel Gain		
PU-SU sets	HGA	Proposed Work
5-3	63.5417	64.3863
8-4	149.943	151.205
12-5	185.552	187.439

From above table 4 it is obtained that proposed work Teacher Learning Based optimization genetic algorithm has high channel gain values as compare to the previous HGA [9] work. This is due to the dual learning in TLBO which consider the objective function which learning as well.

Table 5 Power comparison of HGA and proposed work.

Power in dB		
PU-SU sets	HGA	Proposed Work
5-3	2.35984	1.8
8-4	3.9718	2.16
12-5	4.47673	2.08

From above table 5 it is obtained that proposed work Teacher Learning Based optimization genetic algorithm has low power utilization values as compare to the previous HGA [9] work. This is due to the dual learning in TLBO which consider the objective function which learning as well.

V. Conclusions

As CR network has resolved the various issues of the present limited wireless spectrum. Here paper has resolved the issue of subcarrier pairing for the primary units and secondary units. In this work a new genetic approach is utilized named as teacher learning based optimization for the proper pairing. As this approach has two phase learning, so obtained pairs are quit efficient on various evaluation parameters. Results are compare with previous existing approach and it was found that proposed work was better. In the future it is highly desired that algorithm need to be developed which can efficiently utilize the available resources with minimum loss.

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