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DETECTING PRIMARY SIGNALS FOR EFFICIENT UTILIZATION OF SPECTRUM USING Q-LEARNING (POSTPRINT)

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14. ABSTRACT
The efficient utilization of underutilized spectrum is the main theme of the current research. The cognitive radio with the help of Q-learning algorithm is used to detect the presence of primary signals and make utilize the spectrum in the absence of primary signals. In this proposed research the Q-learning algorithm helps the cognitive radio to detect the presence of some of the primary signals which could not be detected due to their presence as weak signals and detects as primary signal due to some interference even though no signal is present. Due to failure to detect or false detection of Signals, the spectrum utilization will not be used efficiently. The proposed Q-learning algorithm model identifies previously known signals and learns to detect the signals which otherwise could not be detected and helps for efficient utilization of spectrum. The simulations further confirmed with results obtained through MATLAB gatool.

15. SUBJECT TERMS
spectrum utilization, cognitive radio, radio channels, reinforcement learning, primary user, genetic algorithm

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Detecting Primary Signals for Efficient Utilization of Spectrum Using Q-Learning

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Abstract

The efficient utilization of underutilized spectrum is the main theme of current research. The cognitive radio with the help of Q-learning algorithm is used to detect the presence of primary signals and utilize the spectrum in the absence of primary signals. The proposed Q-learning algorithm model identifies previously known signals and learns to detect the signals which otherwise could not be detected, and helps for efficient utilization of spectrum. The simulations are further confirmed with results obtained through MATLAB gatool.

Key words - cognitive radio, channels, reinforcement learning, primary user, genetic algorithm

1. Introduction

The cognitive radio (CR) is an emerging wireless technology for dynamic spectrum utilization and spectrum reconfiguration [1, 2, 3, 4]. The CR helps efficient spectrum utilization, interference avoidance, better system performance, and spectrum sensing followed by adaptation. The CR can be used as reconfigurable communication device. The CR device may be installed at the base station to detect the presence of other users in the environment. The CR will also be used to alter the frequency, power, modulation, coding, and other transmission parameters in real time. Spectrum detection by CR in real time is based on passive sensing and geo-location with spectrum usage database [15, 16, 17, 18, 19].

Presently, cellular systems are based on fixed channel allocation system [7] called static allocation. Fixed channel allocation is that a set of channels are partitioned and these partitions are assigned to cells. The same frequency is allowed in different cells as long as they maintain without interference. When a call arrives and pre-assigned channel is unused then the channel will be assigned; otherwise the call will be terminated. So the static policy (fixed channel allocation system) cannot meet the real demand and most of the spectrum will be unused. The alternative and more efficient policy is dynamic allocation of spectrum [5, 6, 7, 8, 9]. To make efficient use of spectrum we divide the customers into two groups: high priority or primary users (PU) and low priority or secondary users (SU). The PU always gets the spectrum whenever the user wanted to use. In the absence of PU, the SU may be allowed to use the spectrum, so that the spectrum can used efficiently. That means, if a high priority user enters into the domain, the low priority user must vacate. This arrangement helps for efficient use of the spectrum, but many problems need to be solved. One of the problems is detecting the PU, so that the SU will be moved out. To detect the presence of PU we introduce an agent called cognitive radio (CR), which is situated at the base station and helps the SU to get access to the spectrum.

The CR not only detects the presence of PU but also meets the daily requirements including selection of band, mode, format, and user communication requirements. The CRs are installed at SU level to provide better facilities at SU level without interference at the PU. There are four points outlined in protection of PUs.

- Create no-talk zone between PUs and SUs, where SUs will be silent. The size of the no-talk zone depends on the CR's maximum transmit power. If a CR cannot tell where the primary system's receivers are located, SUs must stay out of the area that is the union of all possible no-talk zones.
- Sometimes the no-talk zone needs to be pushed further to avoid the interference for PUs. The border of no-talk zone must be placed outside the decode radius.
- In the absence of PUs, the SUs must respect the protected area.
- New challenges and new opportunities arise in the presence of multiple users.

The CR technology at SU level will efficiently utilize the unused spectrum at any given time and geographical location [12, 13, 14]. The basic idea is CR terminal can sense the environment and location and adapt its features (power, frequency, modulation, etc.) and allow dynamically reuse the available spectrum. The reinforcement algorithm is used to learn without trained examples. It senses the signals provided as part of its input and new user signal entering the domain which has not seen before. The basic principle of reinforcement algorithm is learning through experience, through bidding environment, and reward for winning and penalty for loose [10, 11].

Two main problems arise in recognizing the PU entering into the domain:

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- failure to detect the presence of PU
- false detection of PU when user does not exist (enter into the domain).

To avoid the failure to detect the PU signal or false detection of PU signal, we may take the help of existing literature which solves similar problems. One of the solutions closely related to the current problem is Q-learning model in reinforcement learning. The Q-learning algorithm solves the problem of detecting the unknown signal entry while entering into the network. Once signal is detected store it in the database, so that similar signal will be detected next time if it occurs.

2. Related Work

The detection of the weak signals from primary transmitters was studied recently by Hoven [17] and showed that signal detection is very difficult if there is uncertainty in the receiver noise variance. The authors suggested the detection will be improved through the use of pilot tone from the primary transmitter. Sahai and Hoven [18] discussed that if the location of primary receivers is unknown, the cognitive radio rely on the weak primary signal to make decisions. Wild et al. [12] took the advantage of local oscillator [LO] leakage power emitted by the radio frequency (RF) front end to locate the primary receivers and guarantee that CR will not interfere with primary receivers. Wild et al. also proposed a low cost sensor based cognitive radio system architecture close to primary receivers to detect the LO leakage. Haartsen [20] proposed that CR techniques are not recommended to deploy in bands where interference sensitive or licensed QoS (quality of service) operations are generally assumed, since the signal levels are expected to be low. Haartsen also suggested that without prior knowledge of the existing service signal signature, it will be very hard for CR to detect such signals. So it requires a new methodology to identify such signals.

The identification of the primary user is based on the signal characteristics. Cabric [2] showed that the detection of weak signal possibly improved significantly with the cooperation of CRs. Cabric discussed three techniques, namely, matched filter, energy detector and cyclo-stationary feature detection, to identify the primary signal through the received signal strength. In matched filter, the CR needs the prior knowledge of the primary signal at both MAC and PHY layers. The disadvantage is that CR requires a dedicated receiver for every primary user of a class. The matched filter can be simplified through energy detection which uses Fast Fourier Transformation. The disadvantages of implementing energy detectors are: they are highly susceptible to unknown or changing noise levels. Second, the energy detectors do not differentiate between modulated signals, noise and interference. Third, the energy detectors do not work for spread spectrum signals. Cyclo-stationary feature detection can be used for detection of a random signal with particular modulation type in a background noised and other modulation signals. The cyclostationary signals exhibit correlation between widely spread spectral components due to spectral redundancy caused by periodicity. In spite of these techniques, the cooperative spectrum sensing may be useful if the neighboring cognitive radios were programmed (calculate the overheads) to provide the needed information.

The primary user signal is detected by its signal characteristics or signature [12, 13]. The current artificial intelligence (AI) techniques using rule-based systems, neural networks, and stochastic models will help to detect the signals with known signature. But current methods may have problems to detect the signals deviated from known signature. Most of the wireless signatures have either static signatures (previously known) or dynamic signatures (deviated from known signature). The hard to detect signatures require many times cryptographic models or prepare the experimental models to detect them.

In order to communicate successfully, the radio must first be configured to fit the specific channel; second, the radio must support user required service types, like voice or data; third, above everything else are the regulatory requirements the radio must obey to operate legally in any band and geographic location. To provide best performance the radio needs cognitive engine (CE) to analyze the physical link, user demands, and regulatory regimes and it must balance multiple objectives and constraints. Maldonado [21] showed that genetic algorithms are well suited to solve multi-objective optimization and decision problems (MOGA- multi-objective GA) and the preliminary experiment showed improvement of 20 dB in the ISM band's SINR (Signal to Noise Ratio) using CR technique. Rondeau [22] used GA approach for wireless system and showed that the set of radio parameters designed as genes optimize the user's current needs.

3. Reinforcement Learning and Q-Algorithm

Considerable prior knowledge is required for problems whose solutions optimize an objective function defined over multiple steps. Dynamic programming techniques are able to solve such multistage sequential decision problems with complete knowledge of state space including transition probabilities. But, in most real problems, state transition probabilities are not known. The problems with lack of knowledge will be dealt with reinforcement learning by using each sequence state, action, and resulting state. The current state information is used to incrementally learn the correct value function, which requires the large number of samples. The learning requires long learning process and could not be solved by dynamic programming methods. Reinforcement learning (RL) helps in such situations.

Reinforcement learning (RL) is a way of decision making agents with optimal policies by assigning rewards and punishments for their actions based on the temporal feedback obtained during active interactions of the agent with the system environment. In the RL model depicted in Figure 1, a learning agent selects an action for the system that leads the system along a unique path till another decision making state is encountered. At this time, the system needs to consult with the learning agent for the next state. During a state transition, the agent gathers information about the new state, immediate reward and the time spent during the state-transition, based on which the agent updates its knowledgebase using an algorithm and selects the next action. The process is repeated and the learning agent continues to improve the performance. The whole process steps are part of the Q-Learning algorithm or reinforcement learning algorithm. The details of the algorithm are available in Algorithm 1.

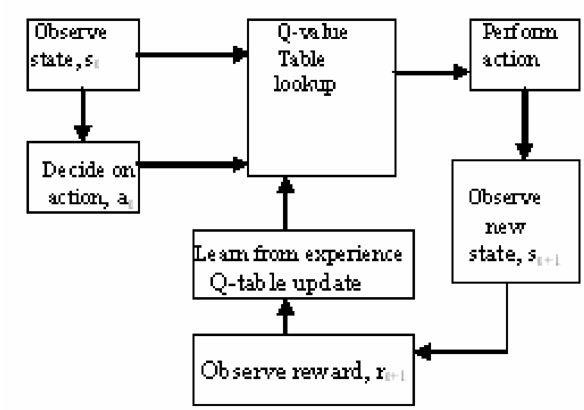

Figure 1. Find a control policy that will maximize the observed rewards over the lifetime of the agent

Algorithm 1

Let s → state, a → corresponding action, and r → reward
Repeat the following steps till no negative power gain:

1. Select an action a at state s and execute it
2. Receive immediate reward r
3. Observe the new state s' and action a'
4. Update the table entry (of rewards and states) for Q(s,a) as:

$Q(s,a) \leftarrow r + \gamma \max Q(s', a')$

$s \leftarrow s'$ where γ is the learning rate ($0 <= \gamma < 1$)

Update the Q table with the new observed signal.

4. Simulations

The Algorithm 1 was implemented using the MATLAB 2006b version. The basic idea of RL is store Q-factor for each state-action pair in the system. Thus, Q (i, a) will denote the Q-factor for state i and action a. The values of Q-factors are initialized to arbitrary numbers in the beginning. Then the system is simulated using the algorithm. An action is selected in each visited state, and immediate reward or penalty will be awarded. The reward or penalty in the transition is recorded as feedback. The feedback is used to update the Q-factor for the action selected in the previous state. The process will continue for large number of transitions. At the end of the phase, called learning phase, the action for Q-factor has highest value and is declared as optimal action for that state.

Most methods for approximating the value function in RL are intuitively represented as matrices. In the current simulation environment, we divide the spectrum (channels) into a square matrix, where each element of the matrix denotes a channel. If the value of an element in the matrix is negative means there is no activity or no signal. The square matrix is developed by introducing dummy states. If the number of channels is 99, then make a channel 100 as a dummy channel with negative value. Then the size of the square matrix will be with 10 rows and 10 columns. The minimum value or strength of a signal starts from the value 0 (-0 is also considered as 0). In the second case, we assumed signal value 0 means no signal and the results of implementation is provided in Table 1B. The Q-Learning algorithm was run with 4 channels (two rows and two columns) to 900 channels (30 rows and 30 columns). The learning rate γ is selected from 0.2 to 0.8. The table 1A and Table 1B are shown with γ =0.2, where the results are reasonably acceptable. In the first step considering signal value 0 as an indication of minimum possible signal (see also the output for 64 channels in Table 1A) and tested with four signals (two rows and two columns). For example if the input to the Q-Algorithm (Algorithm 1) is: -2, 2, -10, 5 with learning factor γ=0.8 the output of the Algorithm generated is (optimum value generated in the Q-table) given below:

0, 88, 0, 100

That is, the optimum values of the state are calculated and stored in the Q-table (database) for each state. Since the value of each state provides the optimum value for that state, the signal detection entirely depends upon the value at the state, because the value is now available as known signal value for the system (CR). The current calculated signal values are combined with the previous known signals, stored in Q-table (Q-database) and then continue the process to detect if any new signal enters in the domain of the primary signal area. Hence it is concluded that, using the reinforcement learning algorithm, the incoming signals will be processed, stored in the Q-table, and combined as part of the previously known signal, which then will be used as part of the known signals to identify the incoming PU signals appropriately.

In the second example, we consider 64 channels (Table 1) for input to the Algorithm 1. The negative values (no signal strength) and positive values (with signal strength) as input are shown in Table 1 and the corresponding output is provided in Table 1A. Alternatively, the signal value 0 is taken as no signal and the output is shown in table 1B.

Table 1: Input to the Algorithm 1

-3	-9	2	-100	0	-300	0	-1
-20	-50	-60	7	-4	7	10	-6
-70	-20	-1	100	-40	50	8	-9
-3	7	3	-9	0	-50	10	-30
9	-30	-22	70	-55	10	7	-20
-44	40	-55	-88	60	10	60	-43
-12	-32	33	7	-77	50	10	-66
50	0	0	10	78	-22	80	55

After execution of the Q-Algorithm (Algorithm 1), the state of the q-table is shown in Table 1A and Table 1B:

Table 1A: Input to the Algorithm 1

0	0	21	0	14	0	12	0
0	0	0	11	0	20	21	0
0	0	0	100	0	62	20	0
0	11	22	0	14	0	21	0
12	0	0	71	0	23	19	0
0	42	0	0	71	23	69	0
0	0	51	11	0	62	21	0
52	4	20	14	88	0	88	70

Table 1B: Input to the Algorithm 1

0	0	21	0	0	0	0	0
0	0	0	11	0	20	21	0
0	0	0	100	0	62	20	0
0	11	22	0	0	0	21	0
12	0	0	71	0	23	19	0
0	42	0	0	71	23	69	0
0	0	51	11	0	62	21	0
52	0	0	14	88	0	88	70

The table 1A and Table 1B values show that state values are updated to their optimum values (improved the signal strength to the level of detection), which further helps to detect the signal detection. The important point is to know about the difference between algorithm output of Table 1A (0 considered as some signal strength) and Table 1B (0 considered as no signal strength). In table 1A the input value of signal 0 is considered as some indication of signal, whereas in table 1B the input value 0 is considered as no signal.

To understand the tables see the corresponding values of Table 1 and Table 1A. The negative values are zeros in Table 1A and positive values are improved to higher frequency status, so that the signal can be represented. If a signal is represented clearly, it will be identified without any failure.

Therefore, the results through tables show that using Algorithm 1 it is possible to detect all possible signals for CR using Q-algorithm of RL model. The current research helps for successful detection of the presence of PU. The characteristics of the signals and visual demo will be considered for future research.

The work of detecting the primary receivers using CR technique is in its initial stage and very few references are available in literature for comparison. One reference is Wild's [12] proposal of Local Oscillator leakage (LO) to detect primary signal. Ben Wild took the advantage of LO power that radio frequency allows CR to locate these receivers and showed the approach is useful in detecting PU. In the current research we used the RL to detect the presence of PU signals, where the approach (detection process) is different from Wild's experimental process, and it is not possible to compare with Wild's results. In the current research, the Algorithm 1 helps for unsupervised learning to detect the minimum strength signal and then stores in Q-table for future reference. The algorithm also helps to detect the absence of the signal, which is a negative value as input in Table 1 and results 0 as output in Table 1A as well as Table 1B.

The results are further verified using the MATLAB *gatool* and found that the results are converging immediately (top left part of Figure 2) and distance between any two individuals is converging after 150 generations or close to 200 generations (top right part of Figure 2). The main parameters used to initialize the *gatool* are given below:

Population Type: Double Vector
Population size: 30
Creation function: Uniform
Selection Function: Stochastic Uniform
Reproduction:
- Elite count: 2
- Crossover fraction: 0.8

Mutation function: Gaussian
Crossover function: Scattered
Migration direction: forward
Algorithm Settings:
- Initial Penalty: 10
- Penalty factor: 100

The results provided in Figure 2, was for 200 generations (test was conducted with 100 generations to 300 generations), with stall generations 500, stall time limit 2000. The immediate convergence (top left part of

Figure 2) and negligible difference between best and mean fitness shows the results are acceptable. As usual, genetic algorithm tool execution requires more time compared to conventional programming (in MATLAB language or Java or C), but produces near optimal solutions to any NP complete problems.

The first part (top left) of the figure displays the fitness function (fitness function is required for the objective function that we want to minimize). Best fitness plots the best function value in each generation versus iteration number. The second part of the figure (top right) plots the average distance between individuals at each generation. The third part (bottom left) of the figure plots the expected number of children versus the raw scores at each generation. Finally, the fourth part (bottom right) plots a histogram of the scores at each generation.

It is observed from Figure 2 that the average distance between two individuals is very close after 150 generations (right top part of Figure 2). The *gatool* results support the Table 1A and Table 1B of RL output since it converges immediately as shown in the first part of Figure 2 and fitness of each individual is same (see part 4 of figure – right bottom).

5. Conclusion

The proposed model using the Q-learning algorithm helps to detect the primary signals. Appropriate detection of primary signals is very important for efficient utilization of the spectrum. Q-learning algorithm learns basing on the data presented to the system (algorithm) by using reward and penalty principle. The algorithm was implemented and results were presented in Table 1A and Table 1B. The results are further confirmed using the MATLAB *gatool*. The *gatool* results show the system converges after 150 generations (Figure 2 - top right). The *gatool* results of bottom right figure further show that the fitness of each individual is same at the end of 200 generations, means the system converges and best possible chromosomes were generated. That is the best possible signal detection possible at that point. It is concluded that the model helps to detect the signals which are hard to detect.

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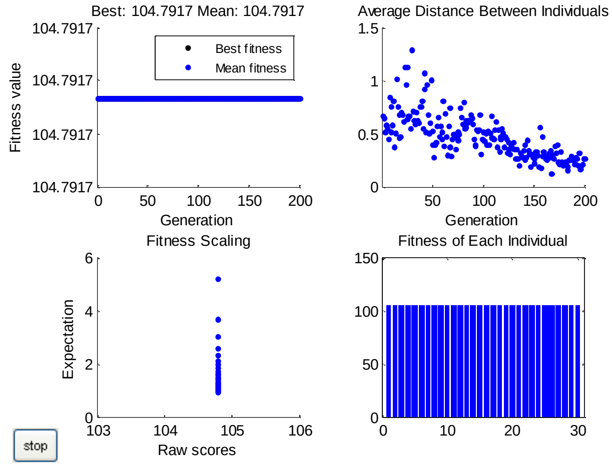

Figure 2. gatool output of Best Fitness, Distance between two Individuals, raw scores between two individuals, fitness of each individual.

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