Adaptive Spectrum Sensing for Cognitive Radio based on Multi-objective Genetic Optimization

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This letter proposes an adaptive sensing period optimization scheme for Cognitive Radio Networks based on a multi-objective genetic algorithm (GA) formulation. Our proposal aims at maximizing the spectrum opportunities as well as minimizing the incurred sensing overhead. The simulation results show that the proposed scheme outperforms the non-optimized proposals by up to 90%. It can also obtain similar or superior performance to compared schemes described in the literature, while keeping the sensing overhead within a target value.

Introduction: Spectrum sensing is a fundamental capability for cognitive radio networks (CRNs) to identify spectrum opportunities [1], i.e., available frequency bands (or channels) for operation by secondary users (SU) while avoiding interference to primary users (PU), who share their spectrum. The discovery of spectrum opportunities comes at the expense of sensing overhead. The sensing overhead corresponds to the time during which the SU must stop data transmissions in order to measure channel's availability. High sensing overhead may compromise the spectral efficiency as the radio is used most of the time for detecting PUs, instead of transmitting data. However, using less frequent sensing may result in interference to PU, due to the delay in the immediate detection of the PU reappearance.

Thus, it is of paramount importance to optimize the sensing period, which determines the frequency that the sensing happens, for each channel, in order to maximize the number of spectrum opportunities with a minimum incurred sensing overhead. In this letter, we propose an adaptive sensing period scheme based on a genetic algorithm (GA) [2] formulation. The proposed scheme ensures that the sensing overhead is always below a user defined upper bound.

Previous work has applied GA-based solutions to CRNs [3][4], but none has used GAs to optimize the sensing periods. Despite the well-known GA large convergence time, solutions to reduce this time have been proposed [5]. In our work, we assume that GA could be adopted at the first stage of the cognitive cycle during the initialization phase, before the radio becomes fully functional. In addition, the GA could also be used to update the sensing periods during normal operation, as a background task, according to dynamic nature of the spectrum.

Channel Model: We assume a SU senses a channel during a sensing time in order to determine its availability for use. The sensing period of the channel i will be represented by x_i. Any idle channel discovered by the periodic sensing becomes a new spectrum opportunity to be utilized by the SU. As in [1][6], we adopt the ON-OFF model (illustrated in Fig. 1) to represent the PU behavior in the context of MAC layer sensing. Thus, the SU can transmit opportunistically while the channel is in the OFF state, i.e., no PU is currently transmitting. The duration of the ON and OFF periods for each channel i is given by exponential distributions with means $1/\lambda^i_{TON}$ and $1/\lambda^i_{TOFF}$, respectively.

Let $S_i(t)$ be the state of channel i, ON (1) or OFF (0), at time t; the sensing process consists of channel sampling at regular time intervals. In order to determine the optimal set of sensing periods for the channels, our proposal uses instantaneous sensing samples as input to the GA.

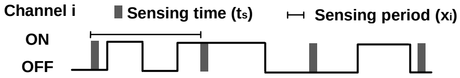

Fig. 1 *ON-OFF Model with Sensing Time and Sensing Period concepts*

GA and Problem Formulation: GA is a search algorithm based on the principles of Darwinian survival of the fittest in the natural evolution. It relies upon evolving a set of solutions, represented by the so-called chromosomes, over a period of time. Eventually, through the GA operators (selection, crossover, and mutation) a good solution will be found by combining different possible solutions [5]. In the proposed GA formulation, each individual or chromosome j, represented by $X^j = [x_1, x_2, x_3, ..., x_N]$, is formed by N parcels as depicted in Fig 2, where $j = 1, 2, 3.., L$, N and L are the number of channels and population size, respectively. Thus, each parcel i, with binary encoding, represents the sensing period for the channel (Ch) i.

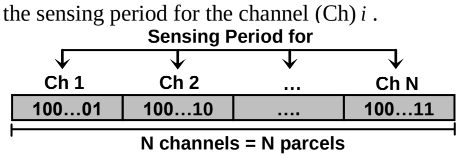

Fig. 2 *Chromosome structure*

We used Pareto strategy to evaluate the solutions to the problem (i.e., the individuals) during the evolution process, since the determination of the set of sensing periods is a multi-objective problem. Thus, the optimization is based on the concept of dominance [2]. In our approach, the dominance evaluation function is based on the number of discovered opportunities (Op), as defined in Eq. (1). Moreover, the individual's evaluation takes in account the incurred sensing overhead (Ov), which is given by Eq. 2.

$$Op(X^j) = \sum_{i=1}^{N} \sum_{h=1}^{M} S_i(x_i h) \tag{1}$$

$$Ov(X^j) = \sum_{i=1}^{N} \frac{t_s}{x_i} \tag{2}$$

where $S_i(x_i h)$ is the state of the channel i at the time instant $x_i h$, with h varying from 1 to M. M is the total number of samples of the channel i with sensing period x_i; t_s is the sensing time.

During the evaluation process, the fitness value for each individual j is defined by computing the number of individuals dominated by j in the population, $DN(X^j)$, as described in (3), where $\equiv (\cong)$ means dominance (non-dominance). Moreover, an evaluation is carried out to determine whether this particular individual has an overhead rate equal or less than a user-defined threshold (Th_{ov}), as defined in (4). Where $\delta_{ov}(X^j)$ is equal to zero if the individual j has an overhead rate greater than Th_{ov} and equal to one otherwise.

$$DN(\mathrm{X}^j) = \sum_{j=1, j\neq r}^{L} \begin{cases} 1\ ,\ \mathrm{X}^j \equiv \mathrm{X}^r \\ 0\ ,\ \mathrm{X}^j \cong \mathrm{X}^r \end{cases} \tag{3}$$

$$\delta_{ov}(X^J) = \begin{cases} 1\ ,\ \mathrm{Ov}(X^J) \leq \mathrm{Th}_{ov} \\ 0\ ,\ \mathrm{Ov}(X^J) > \mathrm{Th}_{ov} \end{cases} \tag{4}$$

Thus, the fitness value of each individual j is given by (5).

$$fitness(X^j) = \delta_{ov}(X^j) + DN(X^j) \tag{5}$$

Hence, the optimization problem of spectrum sensing period can be formulated as:

$$\underset{j\in\{1,2,3,..,L\}}{Max}\ fitness(X^j) \quad subject\ to \quad \begin{cases} x_i > 0,\ x_i \in X^j,\ i = 1,2,3,...,N \\ Ov(X^j) \leq\ Th_{ov} \end{cases}$$

Genetic Operators and Evaluations: For the selection operator, we adopted the roulette wheel [2]. We used the uniform operator for crossover operation, with crossover rate equals to 0.8. The bit one was the mutation operator adopted, with mutation rate equals to 0.01. The number of generation, configured as 300, was the stop criterion for the GA. The resolution used to represent the individual and the population size were set to 10^{-10} and 100, respectively.

We adopted three simulation instances that differ in terms of the number of channels (3, 6, and 9 channels) in the evaluation. We analyzed the effectiveness of our scheme by comparing it with the method based on fixed and unique sensing period for all channels [6], as well as with the adaptive method proposed in [1], namely Kim. The sensing and simulation time were set to 20ms and 100s, respectively. The values $1/\lambda^i_{TON}$ and $1/\lambda^i_{OFF}$ are uniformly distributed in [0.5 5.5], as in [6]. The results are presented with 95% confidence level.

Our GA scheme adopts three versions with different values of upper limit for the tolerable user-defined sensing overhead. Thus, the versions denoted as GA10, GA20 and GA40, aim at maximizing the number of opportunities conditioned to sensing overheads lower than or equal to 10%, 20%, and 40%, respectively. The sensing periods in the two instances of the fixed method, Fixed 1 and Fixed 2, are set to 0.5s and 1.0s, respectively. Fig. 3 shows the mean number of transmission opportunities achieved by the schemes. We note that all versions of our scheme outperform the Fixed 1, Fixed 2 and Kim methods.

GA10 improves the spectrum opportunities, on average, by 21.54% and 28.07% for 3 and 9 channels, respectively, and has a similar sensing overhead to the Kim method. It should be noted that as the number of channels increases, e.g. to 9 channels, the number of opportunities also increases for GA20, which achieves 64.68% and 79.88% more opportunities than Kim and Fixed 1 methods, respectively. The best performance was obtained by GA40, which significantly enhanced the number of opportunities by 82.5% and 94.98%, compared with the Kim and Fixed 2 methods, when 9 channels are considered.

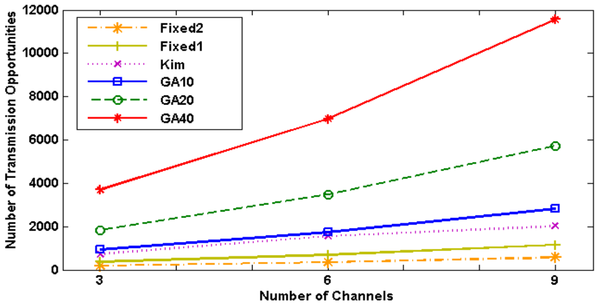

Fig. 3 Average number of transmission opportunities discovered

Fig. 4 shows the average interference time to the PU obtained with each scheme. The GA versions achieved the best performance for all the number of channels. The reduction of the interference time for GA10 was, on average, 8.34% and 26.9%, with respect to the Kim method in scenarios with 3 and 9 channels, respectively. By using the GA20 scheme, the reduction in the interference time was equal to 52.21% and 76.14%, respectively, when compared with the Kim method and the Fixed1 scheme, in the instance of 9 channels. Finally, the GA40 achieved the smallest interference time of all the simulated cases.

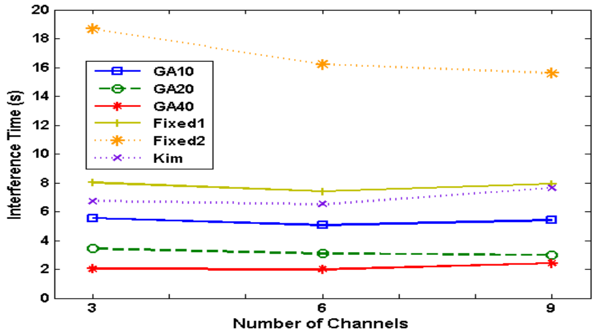

Fig. 4 Interference time

The superiority of our schemes when compared to the fixed ones is due to the sensing period to be adapted according the channel usage pattern. When compared to Kim approach, our strategy is based on an evolutionary process that uses sensing samples to obtain an optimal sensing scheme for the operation. At the same time, the Kim method in [1] adjusts the sensing period on the basis of estimating the average channel behavior, which may not involve significant variations. Furthermore, to determine the sensing period, our approach, through the overhead threshold, indirectly considers the interference caused to the undetected PU, which is overlooked in the other related works.

Conclusion: In this letter we have shown that GA can significantly optimize the spectrum sensing period in CRNs. Our proposal outperforms the non-optimized schemes by up to 90% and it obtained superior performance when compared to a related adaptive proposal, with the advantage that it enables users to specify the permitted sensing overhead that can reflect the interference level tolerated by PU.

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