

Joint Transmission-Sensing Framework Using Changepoint Detection

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Abstract—A cognitive radio (CR) network is reliable by the ability of the secondary user (SU) to maximize the spectrum usage while minimizing the interference on the primary user (PU). This depends on how sensing and transmission are scheduled by the SU. In this paper, we investigate a new joint transmission-sensing framework for a CR system where there is multiple PU appearances and disappearances. Unlike the existing works that sense the spectrum independently frame by frame, we suggest to perform the spectrum sensing sequentially along several frames, using a changepoint detection method. To compute the optimal sensing and transmission times, we introduce a new metric, called the global cost, that gives a trade-off between interference and spectrum waste. The optimal parameters values are studied in detail, with respect to the signal to noise ratio (SNR) and the primary users statistics.

Index Terms—cognitive radio, joint transmission-sensing, changepoint detection, interference, spectrum waste.

I. INTRODUCTION

Dynamic spectrum access (DSA) is envisaged to solve spectrum scarcity faced in wireless communications. Cognitive radio (CR) is a promising technology for DSA because it allows a secondary user (SU) to opportunistically use the spectrum allocated to a primary user (PU) that does not fully use this spectrum. Spectrum sensing is the process that allows the SU to be aware of the spectrum occupancy in order to decide whether to transmit over the spectrum or to release it for the PU [1].

It is impossible to simultaneously transmit data and sense the spectrum for a SU hardware that does not use full duplex techniques. For this reason, the current CRs use an approach based on periodic sensing [2]. Time is split into blocks or frames where an amount of time is allocated to spectrum sensing and another to data transmission. Obviously, the longer the sensing time, the more accurate the spectrum sensing outcome is, but there will be too much spectrum waste if the sensing time is too long. In contrast, the shorter the sensing time, the more time we have for transmission but a too short sensing time will induce too much interference because of sensing inaccuracy. Therefore, there should be a trade-off between the sensing duration and the transmission duration [3].

This topic is abundantly covered by the literature. Most of the existing works assume a sense-then-transmit strategy. The CR frame begins with the sensing period, and if the PU is detected to be absent, the transmission period is used for transmitting. If the PU is detected to be present, there is no transmission until the next frame, where spectrum sensing is performed again. Energy detection is often used as the spectrum sensing method because of its simplicity. While some

authors derive the optimal sensing time for a fixed frame duration [4], others jointly optimize the sensing and transmission durations [5], [6]. For example, the optimal sensing time that maximizes the SU throughput with the constraint of interference to the PUs is derived in [4]. Authors in [5] propose a periodic sensing scheduling scheme and found the optimal sensing period and sensing time that minimize the sensing overhead and average detection time. In [6], a joint optimization of sensing and transmission times is performed to maximize the energy efficiency, subject to spectrum sensing accuracy and limited interference. Unlike the previous works that only use a block-based sensing (energy detection), authors in [3] investigate the throughput-sensing trade-off for CR networks when quickest sensing (or changepoint detection) is used. Always assuming a sense-then-transmit strategy, they compute the optimal frame length that maximizes the throughput and conclude that quickest sensing could achieve higher throughput than block-based sensing, while requiring shorter frame length and sensing time. Note that an independent quickest sensing is carried out in each frame.

In this work, we suggest a new joint transmission-sensing framework using changepoint detection. Unlike the previous works that perform a new spectrum sensing at the beginning of each frame, to detect the current channel state, we propose to sense the spectrum sequentially along several frames, in order to detect changes in the channel state. This choice is motivated by the fact that if the spectrum occupancy does not change too quickly, we can combine observations at successive frames to detect a change. This will result in less time allocated for sensing per frame than in the case of independent sensing at each frame. To achieve this, not only the duration of observation in each frame, but also the period should be carefully chosen. Our goal is thus to find the optimal parameters (sensing time, frame size) for the joint transmission-sensing framework. Our main contributions are the following:

- We first design a new joint transmission-sensing framework based on sequential changepoint detection.
- Then, we introduce the global cost metric, inspired from the global penalty [7], that jointly evaluates the costs of interference and spectrum waste induced by the framework. This metric gives a trade-off between interference and spectrum waste, and is used to compute the optimal parameters.
- For a fixed frame size, we derive the optimal sensing time when the SNR is known, and then we show how to derive a range of optimal sensing times when the SNR is unknown but lies in a considered interval.

- Finally, we perform a joint optimization of sensing time and transmission time.

The rest of the paper is organized as follows. The system model of the joint transmission-sensing framework is introduced in section II. Section III presents some performance metrics and formulates the optimization problem. Then, in section IV, we carry out some simulations and give some numerical results for the joint optimization of sensing and transmission times. Finally, Section V concludes the work and offers a discussion.

II. SYSTEM MODEL

A. System Description

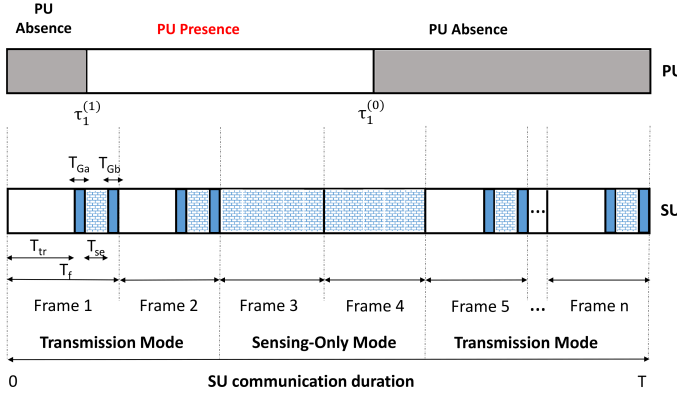


Fig. 1: Joint transmission-sensing system model.

We assume a CR system with multiple geographically-separated fixed PUs transmitting in a frequency band, and a mobile SU, which tries to access the same band opportunistically. As it moves, the SU may enter or leave the coverage area of the different PUs, and the spectrum occupancy will change. We consider that the SU is communicating during a certain amount of time T , during which there may be several PU appearances and disappearances. Let us denote by $\tau_i^{(1)}$ the i^{th} PU appearance time and $\tau_i^{(0)}$ the i^{th} PU disappearance time, which are assumed to be a priori geometrically distributed with parameter p . The SU should not only quickly detect the spectrum release in order to start the secondary communication, but also quickly detect a PU appearance to avoid interference. For this reason, it should be continuously measuring the activity in the band to maximize the use of spectrum opportunities and minimize interference on PUs. Without loss of generality, we assume that the SU looks at only one band but the same reasoning applies for a multiband system.

We consider the joint transmission-sensing scheme shown in Fig.1, where the communication time T is split into n frames of duration T_f ($T = n T_f$). Unlike the existing works that sense the spectrum on a frame by frame basis (one frame at a time, independently from the others), we suggest sequentially performing the spectrum sensing over successive frames. That means we do not take an independent decision at each frame, but we sequentially combine observations at several frames, to detect a change in the spectrum. The SU has two operation modes. The *sensing-only mode* (SOM) is turned on when the spectrum has been detected to be busy. In this mode, the whole frame is used for spectrum sensing until

the next change detection. When the spectrum is detected to be free, the SU switches to the *transmission mode* (TM). In the transmission mode, each frame is composed of a transmission block of time T_{tr} and a sensing block of time T_{se} . They are separated by guard blocks of times T_{Ga} and T_{Gb} , to allow switching between both operations, as only one half-duplex (Radio Frequency) RF chain is used. A frame duration is thus given by $T_f = T_{tr} + T_{se} + T_{Ga} + T_{Gb}$.

B. Spectrum sensing

The signal observed by the SU is denoted by $y_k[m]$, where $k = 1, 2, \dots, n$ is the frame index, and m is the sensing sample index within the frame. When the SU is out of the PUs ranges, $y_k[m] = w_k[m]$, where $w_k[m]$ is the Additive White Gaussian Noise (AWGN) sample at the frame k . When it is within a PU range, $y_k[m] = s_k[m] + w_k[m]$, where $s_k[m]$ is the transmitted signal affected by the channel. It is assumed that $s_k[m]$ and $w_k[m]$ are independent circularly symmetric complex Gaussian variables, $s_k[m] \sim \mathcal{CN}(0, \sigma_s^2)$, $w_k[m] \sim \mathcal{CN}(0, \sigma_w^2)$, and independent of each other. To keep the model simple, we assume that the received signal power σ_s^2 is constant for all the PUs and that it is perfectly known by the SU. It is supposed that initially, the SU is not covered by any PU signal and it turns on the transmission mode until it detects a PU appearance and switches to the sensing-only mode.

For the spectrum sensing, we use the well-known cumulative sum (CUSUM) changepoint detection algorithm [8] over several frames. A changepoint detection algorithm observes a data sequence and has to decide when there is a change in the distribution of the observed samples. A decision statistic is computed at each time sample, based on the previous samples, and is compared with a threshold. We use the CUSUM variant presented in [9] but with a slight modification. Instead of computing a decision statistic at the sample scale, we do it at the frame scale to avoid the complexity of taking multiple decisions per frame. Depending on the current mode, the sensing samples of each frame ($y_k[1], \dots, y_k[T_{se}]$ in the TM and $y_k[1], \dots, y_k[T_f]$ in the SOM) are combined to form one single sample z_k , which is then input to the CUSUM algorithm. This is done for every frame from the beginning of the current mode. We compute z_k by doing the average power of the sensing samples, which is a simple combining scheme that helps reducing the noise power. The spectrum sensing scheme is depicted in Fig. 2. At the end of each frame, the

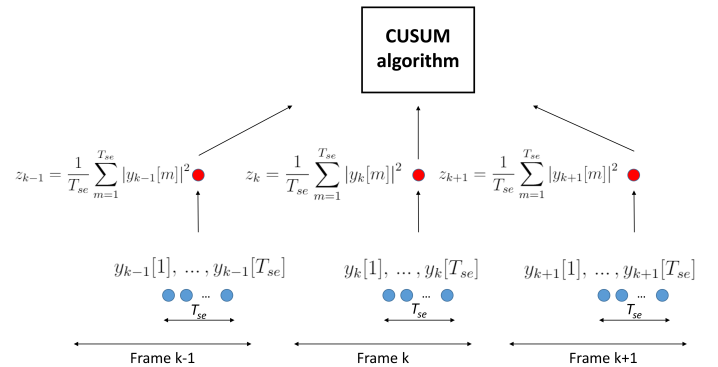


Fig. 2: Spectrum sensing scheme in the transmission mode.

CUSUM algorithm computes a decision statistic C_j , where j

refers to the current frame, and compares it with a threshold α . The detection time is given by [9]

$$S = \inf\{j \geq 1 : C_j \geq \alpha\}, \text{ with } C_j = \max_{l \leq j} \sum_{k=l}^j \ln L(z_k), \quad (1)$$

where $L(z_k)$ is the likelihood ratio¹ of z_k . In the transmission mode, $z_k = \frac{1}{T_{se}} \sum_{m=1}^{T_{se}} |y_k[m]|^2$ follows a chi-square distribution with $2T_{se}$ degrees of freedom, because it is the sum of the squares of $2T_{se}$ real Gaussian variables. The probability density functions (PDFs) of z_k in cases of PU absence and presence are thus respectively given by $f_{TM}^{(0)}(z_k) = \frac{z_k^{T_{se}-1}}{(\frac{\sigma_s^2 + \sigma_w^2}{T_{se}})^{T_{se}} \Gamma(T_{se})} \exp(-\frac{z_k}{\frac{\sigma_s^2 + \sigma_w^2}{T_{se}}})$ and $f_{TM}^{(1)}(z_k) = \frac{z_k^{T_{se}-1}}{(\frac{\sigma_s^2 + \sigma_w^2}{T_{se}})^{T_{se}} \Gamma(T_{se})} \exp(-\frac{z_k}{\frac{\sigma_s^2 + \sigma_w^2}{T_{se}}})$, where $\Gamma(T_{se})$ is the gamma function² of T_{se} [10]. In the sensing-only mode, $z_k = \frac{1}{T_f} \sum_{m=1}^{T_f} |y_k[m]|^2$ follows a chi-square distribution with $2T_f$ degrees of freedom. The PDFs $f_{SOM}^{(0)}(z_k)$ and $f_{SOM}^{(1)}(z_k)$ are the same as in the TM, except that T_{se} is replaced with T_f . As in the TM, we try to detect the PU appearance, and in the SOM, we try to detect the PU disappearance, the likelihood ratios in both modes are differently defined. They are given by

$$L(z_k) = \begin{cases} \frac{f_{TM}^{(1)}(z_k)}{f_{TM}^{(0)}(z_k)} = (\frac{\sigma_w^2}{\sigma_s^2 + \sigma_w^2})^{T_{se}} \exp(\frac{z_k T_{se} \sigma_s^2}{\sigma_w^2 (\sigma_s^2 + \sigma_w^2)}), & \text{if TM} \\ \frac{f_{SOM}^{(0)}(z_k)}{f_{SOM}^{(1)}(z_k)} = (\frac{\sigma_s^2 + \sigma_w^2}{\sigma_w^2})^{T_f} \exp(\frac{-z_k T_f \sigma_s^2}{\sigma_w^2 (\sigma_s^2 + \sigma_w^2)}), & \text{if SOM} \end{cases}$$

III. JOINT TRANSMISSION-SENSING FRAMEWORK

A. Performance Metrics Derivation

In this section, we introduce some metrics in order to evaluate the performance of the joint transmission-sensing framework. In CR, the amount of interference caused on the PUs and the amount of spectrum opportunities used by the SU are two important criteria to assess how robust the sensing is. It is profitable to maximize the SU spectrum usage while minimizing the interference on the PUs. Because both situations are antagonist, a good compromise should be found.

Interference and spectrum waste are caused by errors on PU appearance and disappearance detection. On one side, when a PU appearance is detected with a delay or completely missed or when there is a false alarm on a PU disappearance (earlier switching to the transmission mode), this will create interference. This is depicted in Fig. 3. On the other side, when a PU disappearance is detected with a delay or missed or when there is a false alarm on a PU appearance, this will create a spectrum waste. Moreover, the time block allocated for sensing and guard times when the PU is absent, should also account for spectrum waste because it could be used for transmission. These scenarios are shown in Fig. 4. All this considered, we define the total interference time and total spectrum waste time metrics during the SU communication time T , as T_{int} and T_{sow} .

Let us denote the average total duration of interference and spectrum waste by $\bar{T}_{int}$ and $\bar{T}_{sow}$. Aiming to simultaneously minimize the total interference on the PU and maximize the

¹ l is the time sample after which, $\ln L(z_k)$ has consistently shown positive values, meaning that a change has probably occurred [9].

² $\Gamma(T_{se}) = (T_{se} - 1)!$

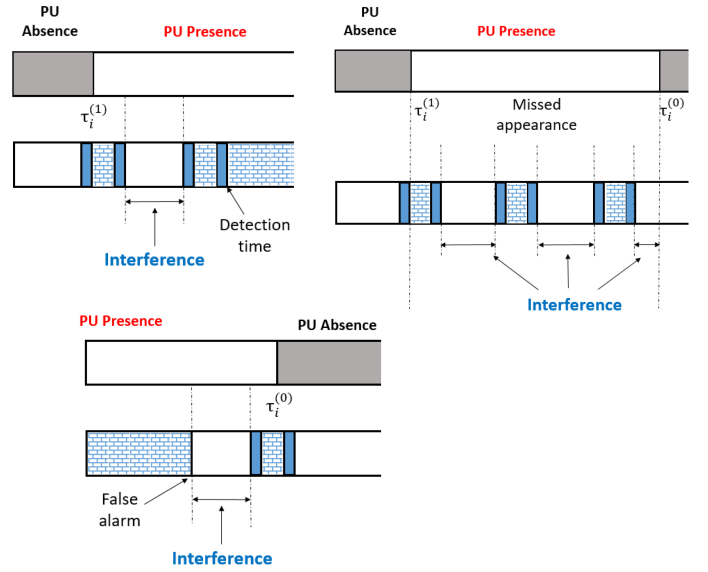


Fig. 3: Interference scenarios.

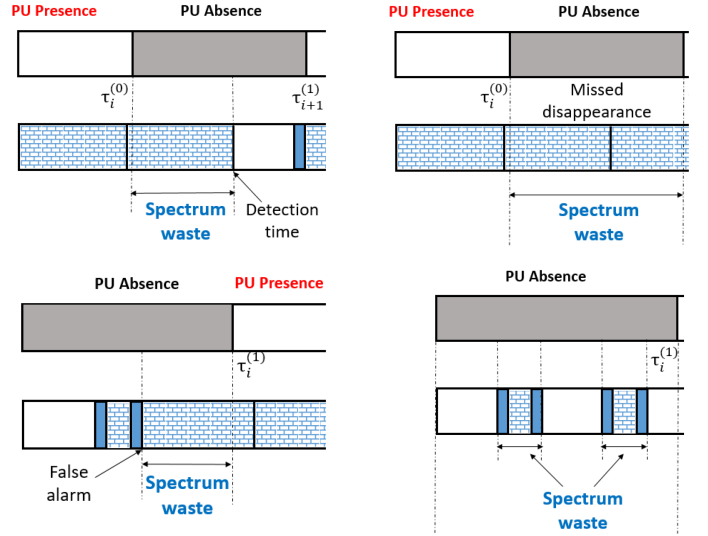


Fig. 4: Spectrum waste scenarios.

spectrum opportunity, we suggest a new performance metric, called the *global cost*. It is obtained by assigning a cost C_{int} to $\bar{T}_{int}$, and another cost C_{sow} to $\bar{T}_{sow}$. The global cost G_C is thus given by

$$G_C = C_{int} \bar{T}_{int} + C_{sow} \bar{T}_{sow}. \quad (2)$$

This metric is inspired from the global penalty metric [7], derived in the case of only one PU appearance detection. It will help deriving the optimal parameters that give a good balance between interference and spectrum waste.

B. Optimal Transmission-Sensing

We define the optimal transmission-sensing scheme as the one that minimizes the global cost induced by the SU. It is given by the following optimization problem:

$$\arg \min_{T_{tr}, T_{se}} G_C(T_{tr}, T_{se}) \quad (3)$$

We thus want to find the optimal transmission duration T_{tr} and sensing duration T_{se} that minimize the global cost G_C . The frame duration T_f is not fixed but is indirectly optimized.

IV. SIMULATIONS & NUMERICAL RESULTS

In this section, we perform some simulations to evaluate the performance of the proposed joint transmission-sensing framework, under various parameters values. Then, some strategies are suggested to jointly compute the optimal parameters values.

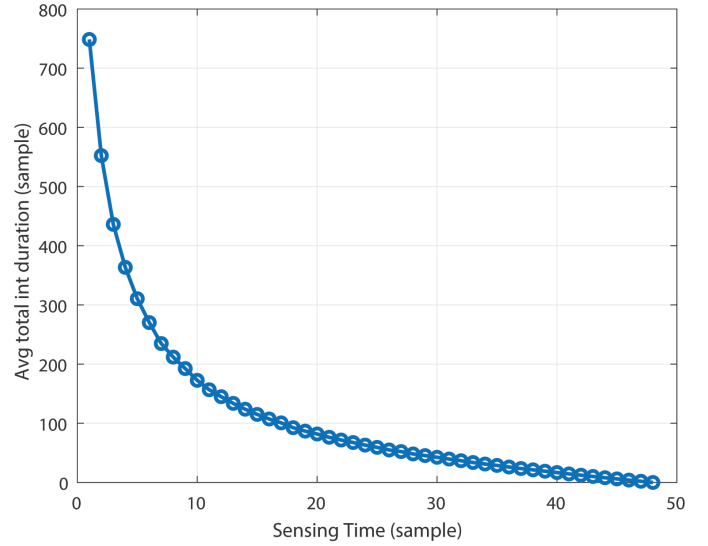
A. Optimal sensing time and transmission time for a fixed frame size

Initially, we assume that the frame size T_f is fixed, and we try to find the optimal sensing time T_{se} (and thus the optimal transmission time T_{tr}) that gives the minimum global cost. We consider the following parameters values for the simulations³: $T = 2500$ samples, $T_f = 50$ samples, $n = 50$ frames, $T_{Ga} = T_{Gb} = 1$ sample, $\alpha = 3.5$, $\text{SNR} = 0$ dB, $C_{int} = 0.5$, $C_{sow} = 0.14$ and $p = 0.003$. It is worth noting that we choose neither too large nor too small values for p in the simulations because of two reasons. A large value of p means fast changes and this is not practical for CR because the SU will not be able to use the spectrum. Inversely, a small value of p implies longer simulations.

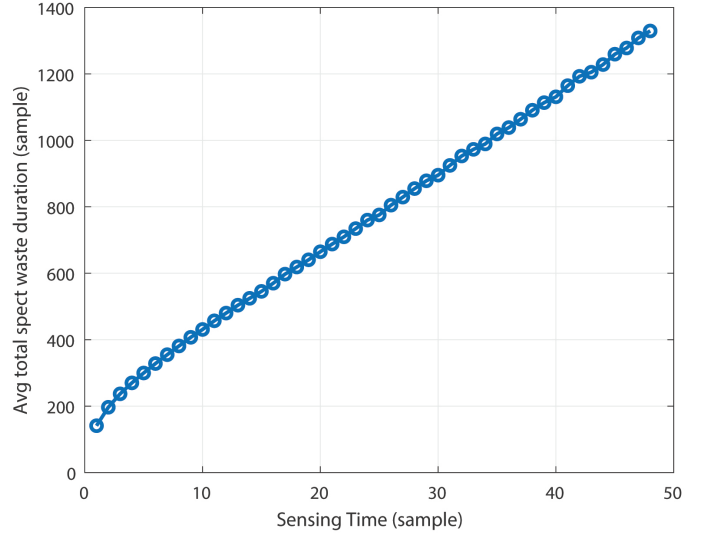
We compute the averages of the performance metrics by using Monte Carlo simulations with 10000 realizations. We first plot the average total interference and spectrum waste metrics with respect to the sensing time. On one side, the average total duration of interference is a monotonically decreasing function (Fig. 5a). This is due to two reasons: first, when more samples are used for sensing, the PU appearances are quickly and well detected so that the interference is reduced; second, increasing T_{se} leads to a decrease of the transmission time T_{tr} and consequently a decrease of the potential time of interference with PUs. On the other side, the average total duration of spectrum waste is an increasing function of T_{se} (Fig. 5b), because using more samples for sensing will decrease the time allocated for transmission and thus increase the amount of time wasted while the spectrum was free.

The optimal sensing time is the one that will give a good compromise between interference time and spectrum waste time. To obtain it, we plot the G_C vs T_{se} curves for a fixed frame size. The optimal sensing time varies with respect to the received SNR as it can be noticed in Fig. 6, where the simulation is done for $\text{SNR} \in [0, 15]$ dB. When the SNR increases, the optimal T_{se} decreases, which means that the higher the SNR is, the less we need samples for reliable spectrum sensing and the more we have time for interference-free transmission.

As we assume in Section II that the SNR is perfectly known by the SU, the optimal sensing times for different SNR values can be pre-computed and stored in a table, and then recovered during the joint transmission-sensing operation. However, we do not know how to deal with practical situations where the SNR is unknown by the SU. To solve this issue, we suggest to derive a range of optimal sensing times that keep the global cost to the minimum, with a certain margin β (Fig. 7a). We then compute the intersection of the derived ranges for different SNR values. The resulting range is the optimal



(a) $\bar{T}_{int}$ vs T_{se} .



(b) $\bar{T}_{sow}$ vs T_{se} .

Fig. 5: Average interference and spectrum waste times.

range of sensing times that always keep the global cost to the minimum, when the SNR lies between the considered values. Considering an upper margin of 10 over the minimum global cost, and a SNR ranging from 0 to 15 dB, we obtain the optimal ranges plotted in Fig. 7b. We can observe that if $\text{SNR} \in [3, 15]$ dB, the optimal T_{se} can be chosen in the set $\{7, 8, 9\}$.

B. Optimal frame size for a fixed sensing time

Beside the optimal time allocated for sensing, it is important to consider the sensing period (that is also the frame size) which also has an impact on the performance of the framework. For this reason, we investigate the optimal frame size T_f for a fixed T_{se} . We perform some simulations for fixed values of sensing time T_{se} and total communication time T , while varying the frame size T_f . Considering $T_{se} = 5$ samples, $T = 2500$ samples and $p = 0.003$, we plot the G_C vs T_f curves for various SNR values. As we can see in Fig. 8, the

³The costs are defined using the same rule as in [7].

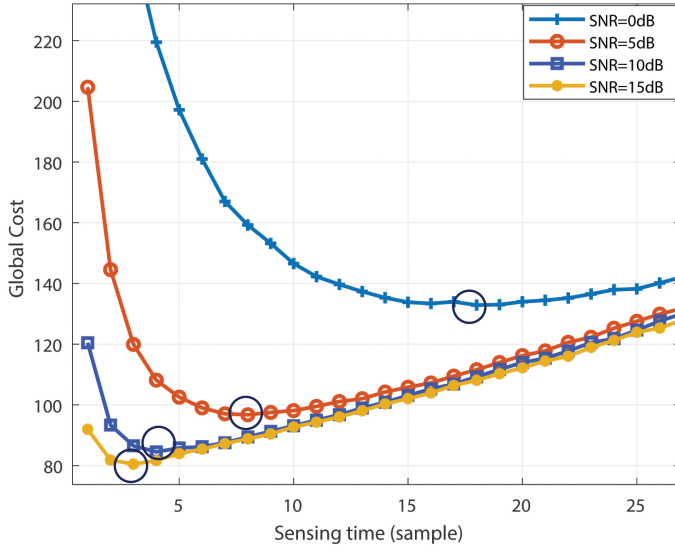


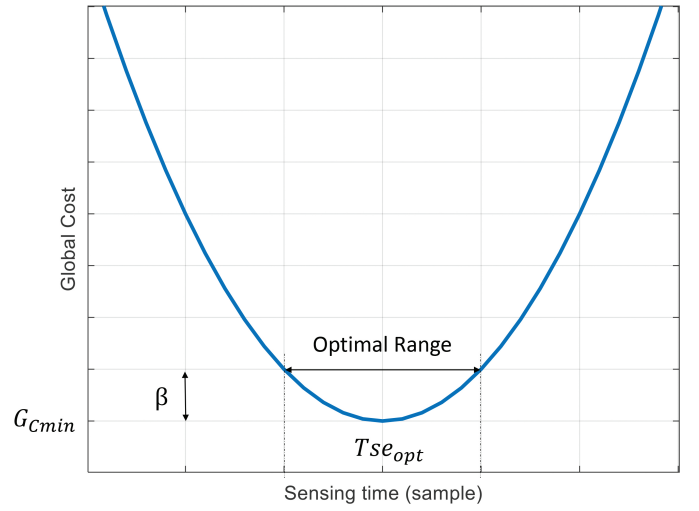
Fig. 6: Global cost (G_C) versus sensing time (T_{se}).

optimal frame size T_f varies slightly with respect to the SNR value. We then plot the same curves for a fixed SNR value (5 dB) but varying p ($p \in [0.001, 0.01]$). It can be noticed in Fig. 9 that the optimal frame size T_f decreases when the probability of PU appearance and disappearance p increases. This means that the more frequent we get PU appearances and disappearances, the more frequent we should perform spectrum sensing and the shorter should be the frame size T_f . To summarize, the optimal frame size depends more on the probability of PU appearance and disappearance than the SNR value. In the next section, we jointly compute the optimal frame size and sensing time.

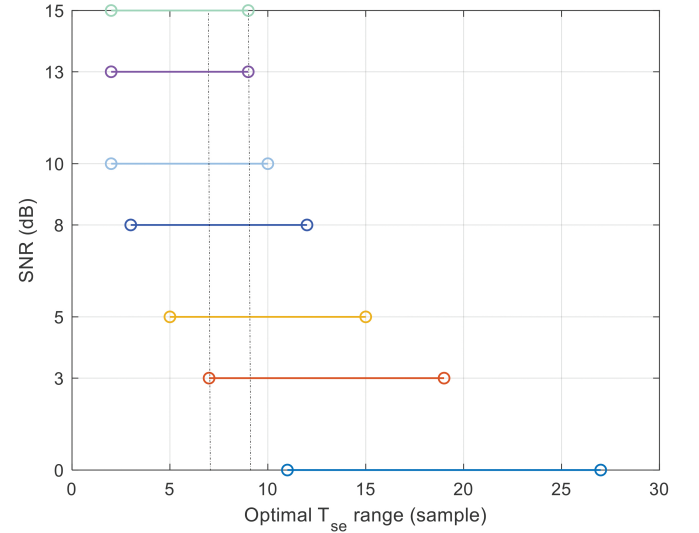
C. Joint computation of optimal frame size and sensing time

In the two previous sections, we compute the optimal sensing time by fixing the frame size and vice versa. Here we jointly optimize both parameters.

First, we use exhaustive search to find the optimal (T_{se}, T_{tr}) couple. The 3D curve of the global cost G_C versus T_{se} and T_{tr} is shown in Fig. 10. We can see that when T_{tr} is increased too much with a small T_{se} , the global cost is increased, certainly because of the interference. The same is observed when T_{se} is increased too much with a small T_{tr} , but this is due to the spectrum waste this time. It is also noticed that there is a minimum global cost and it is obtained for $(T_{se} = 4$ samples, $T_{tr} = 17$ samples). With further simulations, it can be shown on the one hand that when the SNR is varied (from 0 dB to 20 dB) with $p = 0.003$, the T_{se} of the optimal (T_{se}, T_{tr}) couple varies a lot (from 12 to 1), while the T_{tr} slightly varies (from 17 to 14). On the other hand, when p is varied (from 0.001 to 0.01) with SNR = 0 dB, the T_{tr} of the optimal (T_{se}, T_{tr}) couple varies a lot (from 35 to 9) while the T_{se} has a constant value (4). This result confirms what was already observed in the previous section. This leads us to conclude that the optimal sensing time depends more on the SNR value while the optimal transmission time (or equivalently the optimal frame size) depends more on the PU probability of appearance and disappearance. A similar result is found in [11], where it is noticed that the optimal sensing



(a) Computation of optimal range of sensing times.



(b) Optimal ranges for various SNR.

Fig. 7: Range of optimal sensing times in unknown-SNR situation.

time is much less sensitive than the optimal transmission time when primary activity parameter changes.

Second, we propose a simple strategy to jointly choose both optimal parameters values, because of the time complexity of exhaustive search. We suggest the following steps:

- We initialize the optimal sensing time: $T_{se} = 1$ sample.
- Then, for the initial T_{se} value, we find the optimal transmission time T_{tr} , using Monte Carlo simulations.
- For the optimal T_{tr} computed, we find the corresponding optimal sensing time T_{se} , using Monte Carlo simulations.
- We repeat the process as long as the global cost decreases.
- We use the last (T_{se}, T_{tr}) couple as the optimal one.

This method is more time-efficient than the exhaustive search (about one third of the simulation time), and shows comparable performance. It is depicted in Fig. 11 where for $p = 0.003$ and SNR = 5 dB, the exhaustive search gives $(T_{se} = 4, T_{tr} = 17, G_C = 85.32)$ and the simple method gives $(T_{se} = 3, T_{tr} = 14, G_C = 85.43)$.

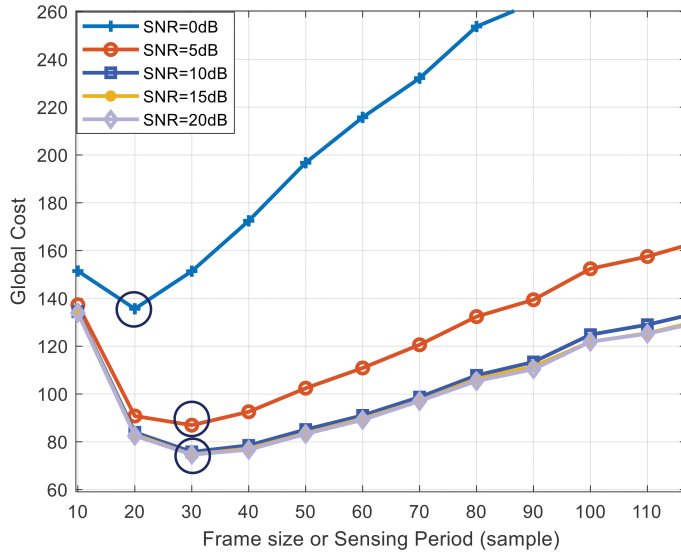


Fig. 8: G_C vs T_f for different SNR values with $p = 0.003$.

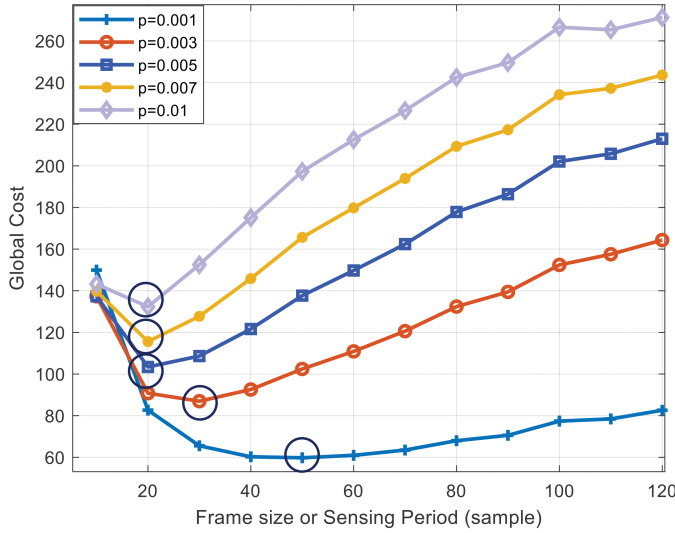


Fig. 9: G_C vs T_f for different p values with SNR=5 dB.

V. CONCLUSION

In this work, a new joint transmission-sensing framework is considered. Using a changepoint detection algorithm, spectrum sensing is performed sequentially over successive frames. The optimal sensing and transmission times are computed and analyzed by means of simulations. Furthermore, it is shown that the optimal sensing time is very sensitive to the SNR, whereas the optimal transmission time is sensitive to the PU statistics.

A potential direction for future work is to jointly optimize the sensing threshold along with the other parameters. Another interesting perspective is to consider a multiband scheme of the proposed framework.

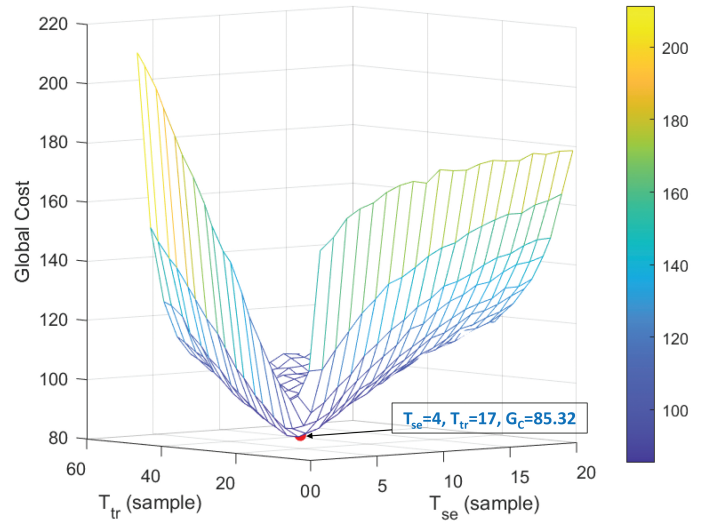


Fig. 10: G_C vs (T_{se}, T_{tr}) for $p = 0.003$ and SNR = 5 dB.

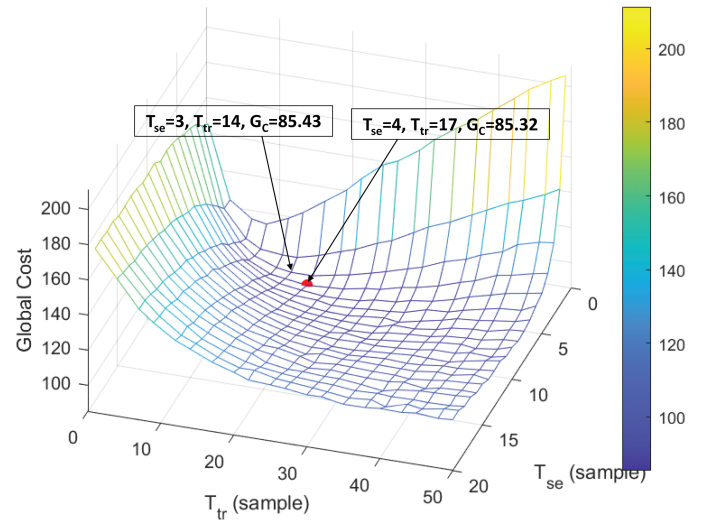


Fig. 11: Optimal (T_{se}, T_{tr}) for $p = 0.003$ and SNR = 5 dB, with both methods.

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