Response to the Reviewer's comments on "SensingThroughput Tradeoff for Interweave Cognitive Radio System: A DeploymentCentric Viewpoint (TW-Aug-15-1167)"

Ankit Kaushik, Shree Krishna Sharma, Symeon Chatzinotas, and Björn Ottersten, Friedich K. Jondral

Dear Editor,

We wish to thank you for your assistance in the review process which has helped us improve our manuscript significantly. We have revised our manuscript addressing all the valuable comments provided by the reviewers. We have highlighted (with blue color) the major changes in the revised paper. The main revisions are described below.

1) We have clarified the definition of the SNR of the primary signals in Section I of the revised manuscript. We define the SNR of the primary signals as the ratio of the received primary power to the noise power at the Cognitive Radio (CR) receiver.
2) To better clarify the application of the proposed SNR estimation technique, we have revised Section I-A of the manuscript including further references related to SNR estimation in the context of CR networks in Section II.
3) To evaluate the SNR estimation performance in case of the imperfect correlation model as suggested by the reviewer, we have revised the results in Fig. 5 (Revised Manuscript) including one additional curve for the case of imperfect correlation model and adapted the text of the Section VII accordingly.
4) We have renamed the MP based MME technique as the asymptotic MME technique and improved its description in the revised manuscript.
5) We have clarified the difference in the performance of the energy detection (ED) and the MME/EME techniques in the presence of spatial correlation in Section VII.
6) We have discussed the possibility of extending this analysis to the time correlated case in footnote 5 and clarified issues raised regarding the asymptotic analysis in footnote 6.
7) We have included further discussion to clarify the considered false alarm rate while comparing

different scenarios in Section VII.

8) We have revised the whole manuscript carefully to avoid any typos, repetitive statements and confusing expressions.

In the following paragraphs, we respond to the reviewers' comments point by point.

Dear Reviewer 1,

Thank you very much for your valuable suggestions and insightful comments on our manuscript. The detailed revisions are listed in the following points.

Comment 1: *In the 2nd paragraph of Section I-A, If the CR is able to estimate the SNR of the primary signals, it can dynamically adapt its coverage area using underlay techniques is not clear. Since in underlay techniques the key is to control the interference caused to the PU, how SNR estimation of the PU signals facilitates the spectrum sharing in underlay techniques? In practical scenarios the channels may not be reciprocal and the transmit power of the PU may not be available at CR.*

Author's Response: To address this concern, we have revised the second paragraph of Section I-A as follows: "In order to implement underlay techniques such as power control at the CR, we need to know the SNR threshold required for the power control algorithm. Furthermore, to calculate the SNR threshold, we need to calculate the distance between the Primary Receiver (PR) and the CR. We consider Effective Isotropic Radiated Power (EIRP) of the Primary Transmitter (PT) as the cognition information at the CR and assume a Line of Sight (LoS) reciprocal channel. Based on EIRP limits of the PT and estimated received SNR of the primary signals, the spatial distance between the PT and the CR can be estimated and subsequently, based on this estimated distance, the secondary network can apply distance-based adaptive power control mechanism to adjust its coverage area. To clarify the above scheme, the following two scenarios can be considered. The first scenario assumes duplex mode of transmission for the PUs i.e., each user interchangeably transmits and receives over time. If we fix the SNR threshold based on estimated SNR over multiple time slots, we can also protect the weakest one assuming they have the same interference threshold [14]. The second scenario considers the simplex mode of transmission for the PUs and a short range wireless communication for both primary and secondary systems provided that interference levels from one system to another are at a similar level. In practice, it may be the case that a spectrum resource is completely left unused within a sufficiently large network coverage area. In this context, the optimal exploitation of spectrum holes depends on the maximally acceptable coverage area of secondary transmission while protecting the primary rate [8]. In such type of systems, it can be assumed that setting SNR threshold for the PT is a reasonable strategy for protecting the PR as well. In this context, based on the estimated PU SNR, suitable underlay techniques such as exclusion zone [15] can be applied."

Comment 2: *More analysis on the applicability of the proposed SNR estimation in both underlay and interweave techniques is preferred, especially how the SNR estimation helps the CRs to adaptively switch between underlay and interweave modes. For example, when PU is detected idle, CR accesses the channel; when PU is detected busy, CR either stays silent or adjusts its coverage to access the channel. Then how to make different decisions accordingly?*

Author's Response: To address this concern, we have added further description to the third paragraph of Section I-A as follows: "In the context of CR networks, SNR estimation can be very useful in switching between underlay and interweave (SS) modes adaptively. In the SS only technique, the SUs are not allowed to access a particular PU channel when the channel is found to be occupied. In this scheme, the secondary network may have very low throughput specifically in heavily occupied spectrum regions. If the CR node has the capability of estimating the PU SNR along with its sensing ability, the SU can access the channel with full power in case of an idle channel and access the channel with controlled power in case of the occupied channel. Based on the link budget analysis and the interference constraint, proper SNR threshold can be determined to guarantee the protection of the PU rate. Subsequently, by comparing the estimated SNR with the SNR threshold, power control mechanism can be implemented at the CR to adjust its coverage area. More specifically, in the SS only techniques, the noise only hypothesis is decided if $\mathrm{SNR} \leq \lambda_1$, λ_1 being the decision threshold and signal plus noise hypothesis is decided if $\mathrm{SNR} > \lambda_1$. When we combine SS with the SNR estimation, we can introduce another threshold λ_2 under the signal plus noise hypothesis in the following way. If $\mathrm{SNR} \leq \lambda_2$, then the CR can transmit in the same channel using the power control algorithm based on the interference threshold of the PU and the CR must stop its transmission when $\mathrm{SNR} > \lambda_2$. Furthermore, the PU SNR knowledge provides channel quality information for the secondary system, which can be further used for implementing adaptive techniques such as adaptive bit loading, handoff algorithms and optimal soft value calculation for improving the performance of channel decoders [16]." Moreover, we have modified the third paragraph of Section II by including more references related to the application of SNR estimation in the context of CR networks.

Comment 3: *I think it is possible to extend the analysis to network scenarios where multiple CRs compete to access the spectrum. Then in adjusting the coverage, the CR needs to consider the constraints from both PU and other CRs. Is there a way to incorporate this analysis?*.

Author's Response: Thank you for providing this interesting scenario. Due to the length constraints of this paper, we have not included this scenario in this paper and we consider the application of the proposed SNR estimation technique in adjusting the coverage in network scenarios incorporating multiple CRs as our future work. In the network scenarios where multiple CRs exist, each CR has to adjust its coverage area based on the interference constraints of the PU as well as the SUs as mentioned by the reviewer. In this paper, we basically focus on SNR estimation technique and based on the estimated SNR, different underlay strategies such as the one suggested by the reviewer can be implemented in adjusting the coverage area of the CR.

Dear Reviewer 2,

Thank you very much for providing valuable suggestions which have helped us improve our manuscript significantly. We have carried out a major revision on the manuscript guided by these valuable comments. The detailed corrections are listed in the following points.

Comment 1: *The sensing algorithms considered in the paper are MME (maximum eigenvalue/minimum eigenvalue) and EME (average eigenvalue/minimum eigenvalue). One of the main results is that the MME and EME performances increases with channel spatial correlation (see Fig. 1). Maybe something is unclear here, because this looks a bit surprising for two reasons. First, in [28] it was shown that the Energy Detection (ED) performance decreases with spatial correlation. Note that energy detection is (average eigenvalue/variance) then not far from EME (where the noise variance is estimated by the smallest eigenvalue only). Then we would expect to a similar behavior for EME and ED. Moreover, if the performance improves with spatial correlation it would be possible for a designer to introduce spatial correlation to achieve better performance[M1] The authors should mandatory clarify why the sensing performance of MME and EME improves with spatial correlation and explain why this is not the case for ED.*.

Author's Response: Thank you for pointing out this to us. We have addressed this concern in Section

VII-B and Remark 7.1 of the revised manuscript. We agree with the reviewer that the contributions in references [32-34] have studied the effect of spatial correlation on the ED technique and their results show that the performance of ED technique degrades in the presence of the spatial correlation. According to our knowledge, only the contribution [12] has investigated the effect of spatial correlation on the performance of eigenvalue-based technique, especially considering the predicted eigenvalue threshold based technique. As noted in reference [12], the performance of the considered eigenvalue-based detection technique improves in the presence of spatial correlation. To clarify this in the revised manuscript, we have added further description in Section VII-B as follows: "Similar to the performance results obtained in [12], we note that the performance of the considered eigenvalue-based techniques improve in the presence of spatial correlation. This is due to the reason that the presence of spatial correlation strengthens the eigenvalues of the received signal's matrix under the $\mathbb{H}_1$ hypothesis compared to the uncorrelated case. Since the contribution of the signal eigenvalues is improved in comparison to the noise eigenvalues in the presence of spatial correlation, the probability of detection improves in the presence of spatial correlation in eigenvalue-based techniques."

As mentioned by the reviewer, the difference between the ED and the EME technique is that the ED technique compares the signal energy to the noise power while the EME technique compares the received signal's energy to the minimum eigenvalue of the received signal's sample covariance matrix. To clarify different effects of spatial correlation on the performances of the ED and the EME/MME techniques, we have added Remark 7.1 in the revised manuscript as follows: "As noted in [32,34], the performance of the ED technique degrades in the presence of spatial correlation. The different effects in the performances of the ED and the MME/EME techniques due to the presence of spatial correlation come from the fact that in the ED, noise power is determined completely by the $\mathbb{H}_0$ hypothesis while the denominator term in MME/EME techniques (i.e., the minimum eigenvalue) is determined from the received signal's covariance matrix under the $\mathbb{H}_1$ hypothesis. More specifically, in the EME/MME techniques, both the numerator and denominator terms vary in the presence of spatial correlation while the noise power does not depend on the spatial correlation for the case of ED."

Comment 2: *The authors have not considered the GRLT-like algorithm (maximum eigenvalue/average eigenvalue) studied in [R1] and [R2] which is very well known for sensing applications and has (much) better performance than MME and EME. [S1] We strongly suggest to add it into the picture: in this way* *the obtained results would be much more useful.*

R1. P. Bianchi, M. Debbah, M. Maida, and J. Najim, "Performance of Statistical Tests for Source Detection using Random Matrix Theory".

R2. B. Nadler, F.Penna, R. Garello, "Performance of Eigenvalue-based Signal Detectors with Known and Unknown Noise Level", ICC 2011.

Author's Response: To address this concern, we have revised Section IV by including Remark 4.1, where we state "It can be noted that GLRT like algorithms such as Scaled Largest Eigenvalue (SLE) (i.e., maximum eigenvalue/average eigenvalue) have been investigated in [39,40]. Furthermore, the effect of noise correlation on different eigenvalue-based blind techniques including the SLE detector has been analyzed in [36], where it is shown that the SLE technique performs better than other eigenvalue-based techniques for a variety of scenarios and even in the presence of noise correlation. Therefore, we simply provide an overview of MME/EME techniques and evaluate their performances in the presence of channel/noise correlation numerically in Section VII." Moreover, we have attached the reference [36] along with this submission. Since the main focus of this paper is on SNR estimation as mentioned in Section I-A, we have included the MME and EME results simply to give an indication about the effect of correlation on eigenvalue-based techniques.

Comment 3: *MP based MME Technique. This technique is presented separately from MME, but maybe it would be better to present it as a technique for asymptotic analysis of MME. If the authors want to present it as an alternative sensing algorithm, they should improve its description. For example, it is unclear if the algorithm has the CFAR property. The authors should better clarify if it they are considering it as an independent sensing algorithm (and in this case improve its description), otherwise it would be better to present it in the MME paragraph by clarifying its meaning [M2].*

Author's Response: To address this concern, we have revised Section IV (Page 12), where we have included the MP based MME technique under the MME heading renaming it as the asymptotic MME technique and further revised its description. As mentioned in Section IV-A, the MME technique included in Section IV-A (1) (modified version) is asymptotic since the bounds for both the maximum and the minimium eigenvalues are calculated based on the asymptotic analysis and the MME technique included in Section IV-A (2) (modified version) is semi-asymptotic in nature since the bound for the maximum eigenvalue is calculated based on the limiting Tracy-Widom distribution instead of the asymptotic distribution while the minimum eigenvalue is evaluated based on the asymptotic analysis. The asymptotic MME technique included in Section IV-A (1) (modified version) does not have Constant False Alarm Rate (CFAR) property since its threshold is not a function of the false alarm rate. However, the false alarm rate obtained while applying this asymptotic threshold in our numerical results was found to be very low in the order of 10^{-2}. The detailed analysis of this technique including the Cumulative Distribution Function (CDF) curves of the decision statistics (i.e., $\lambda_{\max}/\lambda_{\min}$) can be found in reference [21].

Comment 4: *The authors should clarify if their analysis is asymptotic in both M and N, or if it can be valid for finite M, too [M3].*

Author's Response: This comment has been addressed in Section V-A by including footnote 6, where we state "The analysis carried out in this paper is based on the assumption that both dimensions M and N go to infinity with some finite ratio $\beta = N/M$. However, as noted in [24] and [42], the asymptotic analysis provide valid approximations even for finite dimensions while providing more tractable solutions". In [42], it is shown that the asymptotic approximation matches well with the exact finite analysis for the largest eigenvalue-based sensing. Furthermore, it should be noted that if only one dimension of the sample covariance matrix goes to infinity, different analysis needs to be carried out.

Comment 5: *The authors have not considered the case of time correlated channel and noise which is more interesting for practical sensing. They should at least discuss if and how it is possible to extend their results to this case. [S2]*

Author's Response: This concern has been addressed by revising the footnote 5 in Section III-C, where we state "The analysis presented in this paper can be straightforwardly extended to the time correlated noise/channel case assuming the exponential correlation model still holds. In this case, the one-sided correlation model can be applied on the right hand side of the noise/channel matrix instead of left hand side".

Comment 6: *The presented SNR estimation performs better if the module is aware of channel/noise estimation. The authors should clarify if the exact correlation model must be known and at which degradation may occur in case of imperfect model. [M4]*

Author's Response: To address this comment, we have revised the results in Fig. 5 including one additional curve for the case of imperfect correlation model and adapted the text of the Section VII (pages 22-23) as follows: "To evaluate the performance of the proposed technique in case of the imperfect correlation model, we consider 10 % static deviation in the considered value of the correlation coefficient for both the channel and noise correlation. Subsequently, we carry out SNR estimation based on the procedure mentioned in Section VI and evaluate the performance using (21) in terms of the normalized MSE versus SNR plot shown in Fig. 5. From the figure, it can be noted that the PU SNR can be estimated with less than 2.5 % normalized MSE error up to the SNR value of 0 dB while considering 10 % imperfect correlation knowledge. At the same value of SNR i.e., 0 dB, the normalized MSE error is about 2.5 % while considering perfect knowledge of both channel/noise correlation. Thus the normalized MSE performance degradation in case of 10 % imperfect correlation knowledge is about 1.7 % at the SNR value of 0 dB. Moreover, it can be noted that this performance degradation increases for lower SNR values and decreases for higher SNR values following performance of the perfect correlation knowledge case beyond the SNR value of 3 dB."

Comment 7: *Finally, the paper contains (few) typos to be corrected (for example "mimimum eigenvalue", "it can be noted in* $[17] - - >$*", "it was noted in [17]", etc.)*

Author's Response: We have addressed this concern in the revised manuscript. Furthermore, we have revised the whole manuscript carefully to avoid any typos, confusing and repetitive statements.

Dear Reviewer 3,

Thank you very much for your valuable comments and suggestions on our manuscript. The detailed corrections are listed in the following points.

Comment 1: *Well written paper and an important piece of research. The only doubt I have is the false alarm rate in the simulations of the first few graphs. Page 18, at the start of the simulation section, this is described (including the footnote 7), however I am not clear how the false alarm is fixed or compared between various channel scenario. It is useful for the readers if the authors can explain how the comparisons are made wrt false alarm rate in fair manner.*

Author's Response: Thank you very much for appreciating our work. We have revised Section VII-B (First Paragraph) to clarify the considered false alarm rate in our simulation results. As mentioned in Section VII-B of the revised manuscript, for the comparison of the MME and EME techniques in the presence of channel correlation in Fig. 1, the false alarm rate was fixed at 0.07 and then detection threshold was calculated using eqns. (7) and (9) respectively. Based on this calculated threshold, probability of detection was calculated numerically. For the comparison of the asymptotic MME in Fig. 2, the decision statistics is probability of correct decision instead of probability of correct detection. The probability of correct decision is calculated using expression $(P(\mathbb{H}_1;\mathbb{H}_1) + P(\mathbb{H}_0;\mathbb{H}_0))/2$ i.e., $(P_d + (1 - P_f))/2$ as mentioned in Section VII-A. In this case, the threshold is fixed and the number of correct decisions under both hypotheses has been considered to evaluate the sensing performance as mentioned in footnote 8. It can be noted that the references [21,24,30,31] also use similar performance metric to evaluate the sensing performance. However, it is always possible to compare the probability of detection by fixing the common probability of false alarm for all the scenarios by adjusting the decision threshold numerically using the CDF curves of decision statistics. This has been explained in detail in reference [21]. In this paper, we focus on SNR estimation technique and we include the MME and EME results simply to provide an indication about the effect of noise/channel correlation on eigenvalue-based techniques.

Many thanks again for your assistance in this review process, which leads to significant improvement of this work. If further revision is required, we would be very happy to address future comments in this manuscript.

Sincerely yours,

Ankit Kaushik

Shree Krishna Sharma

Symeon Chatzinotas

Björn Ottersten

Friedrich K. Jondral